



# STIC Search Report

## EIC 2100

STIC Database Tracking Number: 152981

**TO: Michael B Holmes**  
**Location: RND 5A44**  
**Art Unit: 2121**  
**Thursday, June 02, 2005**

**Case Serial Number: 10/056438**

**From: Emory Damron**  
**Location: EIC 2100**  
**RND 4B19**  
**Phone: 571-272-3520**

**Emory.Damron@uspto.gov**

### Search Notes

Dear Michael,

Please find below an inventor search in the bibliographic and full-text foreign patent files, as well as keyword searches in the patent and non-patent literature files, both bibliographic and full text.

References of potential pertinence have been tagged, but please review all the packets in case you like something I didn't.

Of those references which have been tagged, please note any manual highlighting which I've done within the document.

In addition to searching on Dialog, I also searched EPO/JPO/Derwent.

There may be a few decent references contained herein, but I'll let you determine how useful they may be to you.

Please contact me if I can refocus or expand any aspect of this case, and please take a moment to provide any feedback (on the form provided) so EIC 2100 may better serve your needs. Good Luck!

Sincerely,

Emory Damron

Technical Information Specialist

EIC 2100, US Patent & Trademark Office

Phone: (571) 272-3520

[Emory.damron@uspto.gov](mailto:Emory.damron@uspto.gov)



Set	Items	Description
S1	1694745	IMAGE? OR IMAGING? OR GRAPHIC? OR VIDEO? OR BITMAP? OR BIT- ( ) (MAP OR MAPS OR MAPPED OR MAPPING)
S2	468841	SONOGRA? OR VISUAL? OR ULTRASOUND? OR ULTRASONIC? OR PICTO- RIAL? OR XRAY? OR X( ) (RAY OR RAYS OR RAYED OR RAYING)
S3	418753	PHOTOGRAPH? OR PET(2N)SCAN? OR PETSCAN? OR POSITRON( ) EMISS- ION? OR MAGNETIC? ( ) RESONANC? OR MRI
S4	18245	TOMOGRAPH? OR MAMMOGRA? OR CATSCAN? OR (CAT OR CT) ( ) SCAN? - OR CTSCAN?
S5	1316288	COMPUTER? OR DIGITAL? OR DIGITIZ? OR DIGITIS? OR BINARY?
S6	589117	DATAPROCESS? OR MICROPROCESS? OR CENTRALPROCESS? OR (MICRO OR DATA OR CENTRAL) ( ) PROCESS?
S7	128360	PROCESS?(2N) (MODULE? OR UNIT?)
S8	272	SVM OR SUPPORT( ) VECTOR? OR VECTOR( ) MACHINE?
S9	10617	MACHINE?(2N) LEARN? OR MACHINE( ) VECTOR? OR NEURAL( ) NETWORK? OR ARTIFICIAL( ) (NEURAL? OR INTELLIGEN?) OR BACK( ) PROPAGAT? OR OPTIM?( ) (HYPERPLAN? OR HYPER( ) PLAN?) OR CYBERNET?
S10	42856	PREPROCESS? OR PREANALY? OR PREEXAMIN? OR PREPARS? OR (BEF- ORE? OR PRIOR? OR PRELIMIN? OR PREPARAT?) (2W) PROCESS?
S11	133956	IDENTIF?(3N) (MISSING? OR ERROR? OR ERRONEOUS? OR FLAW?) OR TRANSCOD? OR DATA(3N) (MODIF? OR CONVERT? OR CONVERSION? OR AL- TER? OR CHANGE? OR CHANGING)
S12	6828	TRANSFORM? ? (3N) (RADON OR HOUGH) OR PRECLASSIF? OR PRE( ) (P- ROCESS? OR ANALY? OR EXAMIN? OR PARS? OR CLASSIF?)
S13	370669	TRAIN? OR LEARN? OR EDUCAT? OR INSTRUCT? OR TEACH? OR TAUG- HT? OR DIDACT? OR SELFTEACH? OR AUTODIDACT?
S14	2755893	ANALYS? OR ANALYZ? OR TEST??? OR DETECT?
S15	1582979	MONITOR? OR GAUG? OR RATE? OR RATING? OR SAMPLE? OR SAMPLI- NG?
S16	263856	EXAMIN? OR EVALUAT? OR ASCERTAIN? OR ASSESS?
S17	672589	KNOWN? OR TEMPLAT? OR STENCIL? OR STANDARD? ? OR NORM? ? OR PAR OR PROFILE?
S18	3367767	CONTROL OR CRITER? OR TOUCHSTONE? OR BENCHMARK? OR YARDSTI- CK? OR IDEAL? ? OR PARAGON? ?
S19	4103162	CLASSIF? OR SUBCLASSIF? OR SYSTEM? OR SUBSYSTEM? OR FEATUR- E? OR SUBFEATUR? OR CHARACTERISTIC? OR SUBCHARACTERISTIC?
S20	2367018	ATTRIBUT? OR SUBATTRIBUT? OR SEGMENT? OR SUBSEGMENT? OR CL- ASS?? OR SUBCLASS?? OR SECTION? OR SUBSECTION?
S21	340367	INDEX? OR SUBINDEX? OR CATEGOR? OR SUBCATEGOR? OR SUBDIVI? OR DIVISION?
S22	4735702	SET OR SETS OR RESULT? OR OUTPUT? OR PROCESS?( ) DATA
S23	899459	REALTIME? OR REAL( ) TIME? OR RTOS OR SYNCHRON? OR SIMULTAN? OR CONTEMPORAN? OR LIVE
S24	2127692	IC=(G06F? OR G06E? OR G06K? OR G06T? OR H04N?)
S25	1138	S1:S4 AND S5:S7 AND S8:S9
S26	112	S25 AND S10:S12
S27	651	S25 AND S13:S16 AND S17:S21
S28	282	S25 AND S5:S7(10N)S10:S16
S29	230	S27 AND S28
S30	693	S27:S29 AND S19:S24
S31	227	S29 AND S30
S32	19	S31 AND S23 AND S24
S33	89	S31 AND S17:S18
S34	80	S26 AND S27:S31
S35	41	S25 AND S22(10N)S13:S16 AND S22(10N)S17:S18
S36	36	S25 AND S23(10N)S10:S16
S37	237	S26 OR S32:S36
S38	808852	PR=2000:2005
S39	223	S37 NOT S38
S40	223	IDPAT (sorted in duplicate/non-duplicate order)
? show files		

File 347:JAPIO Nov 1976-2005/Jan(Updated 050506)

(c) 2005 JPO & JAPIO

File 350:Derwent WPIX 1963-2005/UD,UM &UP=200534

(c) 2005 Thomson Derwent

?

40/3,K/1 (Item 1 from file: 350)  
DIALOG(R)File 350:Derwent WPIX  
(c) 2005 Thomson Derwent. All rts. reserv.

012156452 \*\*Image available\*\*  
WPI Acc No: 1998-573364/199849  
XRPX Acc No: N98-446536

Digital image processing using neural network interface -  
involves preconditioning initial image data through image  
concentration conversion module employing memory based conversion  
functions routing conditional data into neural network based image  
processor

Patent Assignee: HITACHI MEDICAL CORP (HITR )  
Number of Countries: 001 Number of Patents: 001  
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week
JP 10255035	A	19980925	JP 9755780	A	19970311	199849 B

Priority Applications (No Type Date): JP 9755780 A 19970311

Patent Details:

Patent No	Kind	Lan Pg	Main IPC	Filing Notes
JP 10255035	A	11	G06T-005/00	

Digital image processing using neural network interface...

...involves preconditioning initial image data through image  
concentration conversion module employing memory based conversion  
functions routing conditional data into neural network based image  
processor

...Abstract (Basic): The digital image processing employs a neural  
network based processor (2) to handle the initial image data input  
into the feed module (1). The processed data are delivered to a  
display device (3) for analysis. The neural network consists of  
the standard multilayer feed forward arrangement with teacher  
signal aided training and readjustment provisions for the individual  
weights associated with each neuron...

...Between the neural network based processor and the feed module, is  
positioned the image concentration conversion module (4) consisting  
of the serially connected multiplier and adder sub-modules served by  
memory based conversion functions. Provision exists to effect an  
inverse concentration correction on the processed data available  
from the neural network based processor. This inverse correction  
procedure employs serially positioned divider and subtractor  
sub-modules related...

...USE - In medical diagnostic and industrial imaging, consumer  
photographic applications...

Title Terms: DIGITAL ;  
International Patent Class (Main): G06T-005/00  
International Patent Class (Additional): G06F-015/18 ...

... G06T-001/00

40/3,K/21 (Item 21 from file: 350)  
DIALOG(R)File 350:Derwent WPIX  
(c) 2005 Thomson Derwent. All rts. reserv.

009293277 \*\*Image available\*\*

WPI Acc No: 1992-420687/199251

XRPX Acc No: N92-320864

Pre - processing in detecting subject image area on radiographic  
recorded sheet - adds framing pixels to boundary of image pixel data  
and inputs resulting data to neural network to produce binary -coded  
data NoAbstract

Patent Assignee: FUJI PHOTO FILM CO LTD (FUJF )

Number of Countries: 001 Number of Patents: 001

Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week
JP 4317263	A	19921109	JP 9185579	A	19910417	199251 B

Priority Applications (No Type Date): JP 9185579 A 19910417

Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
JP 4317263	A		12	H04N-001/40	

Pre - processing in detecting subject image area on radiographic  
recorded sheet...

...adds framing pixels to boundary of image pixel data and inputs  
resulting data to neural network to produce binary -coded data  
NoAbstract

...Title Terms: IMAGE ;

40/3,K/53 (Item 53 from file: 350)  
DIALOG(R) File 350:Derwent WPIX  
(c) 2005. Thomson Derwent. All rts. reserv.

014253589 \*\*Image available\*\*  
WPI Acc No: 2002-074289/200210  
Related WPI Acc No: 1999-302216  
XRPX Acc No: N02-054774

Pattern recognition method for data clustering analysis in machine vision, involves assigning test data point to unambiguous class if test data point groups with several classes or no classes present in training set

Patent Assignee: SANDIA CORP (SAND-N)  
Inventor: MARTINEZ R F; OSBOURN G C  
Number of Countries: 001 Number of Patents: 001  
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week
US 6304675	B1	20011016	US 93174548	A	19931228	200210 B

Priority Applications (No Type Date): US 93174548 A 19931228

Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
US 6304675	B1	31	G06K-009/62		

... unambiguous class if test data point groups with several classes or no classes present in training set

Abstract (Basic):

... Each of the test data points and training data points of respective data sets are selected and placed on each of the two specified positions of a region of...

...or if the test point groups with several classes or no class present in a training set .

... An INDEPENDENT CLAIM is also included for training data set quality verification method...

...Used for data clustering analysis used in machine vision, pattern recognition, unsupervised and supervised machine learning /classification, medical and biological image and data analysis, crop identification from satellite photos, identification of hazardous chemicals in complex environments...

...Enables successfully clustering complex data sets by assigning test data point to unambiguous class of the training data points. Enables achieving human-like judgment for class membership for n-dimensional test points, and the psychophysical-derived inhibitory template applied to the data sets enables the clustering performance. The need of operator-adjustable parameters or extensive neural net training...

...influence circumscribed by the template of the clustering method and the block diagram of the data processor .

THREE  
RELATED  
BOX  
BENEATH

40/3,K/55 (Item 55 from file: 350)  
DIALOG(R)File 350:Derwent WPIX  
(c) 2005 Thomson Derwent. All rts. reserv.

013997999 \*\*Image available\*\*  
WPI Acc No: 2001-482214/200152  
XRPX Acc No: N01-356909

Automatic digitized mammogram analyzing method for detecting  
possible cancerous tissue mass, involves detecting region of interest  
using digitized mammogram and Fourier spatial bandpass analysis

Patent Assignee: LOCKHEED MARTIN CORP (LOCK )

Inventor: OLIVER D R; SHAPIRO G L

Number of Countries: 001 Number of Patents: 001

Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week
US 6246782	B1	20010612	US 97870709	A	19970606	200152 B

Priority Applications (No Type Date): US 97870709 A 19970606

Patent Details:

Patent No	Kind	Lan Pg	Main IPC	Filing Notes
US 6246782	B1	15	G06K-009/00	

Automatic digitized mammogram analyzing method for detecting  
possible cancerous tissue mass, involves detecting region of interest  
using digitized mammogram and Fourier spatial bandpass analysis

Abstract (Basic):

... The region of interest (ROI) is detected using a digitized  
mammogram and Fourier spatial bandpass analysis . The spatially  
bandpassed images of different resolutions of the mammogram , are  
used to identify brightest peak of the ROI, relative to the cancerous  
mass. Context data with ROI attribute information, is extracted from  
the mammogram . Neural network trained for the attributes of  
cancerous tissue region, generates output indicating if cancerous  
tissue mass is present in ROI.

... An INDEPENDENT CLAIM is also included for the automated  
cancerous mass detection system .

...For detecting cancer or other types of lesions in chest X - ray  
film, or cancerous and pre-cancerous cells in a pap smear or biopsy...

...Hybrid optical digital computer approach ensures sufficient  
processing power at moderate cost, to accommodate discriminating  
algorithms, and effective processing speed in real - time  
applications. The system performance such as sensitivity and  
specificity, is improved in the real - time .

...The figure shows the simplified block diagram of the automatic cancerous  
mass detection system .

...Title Terms: DETECT ;

International Patent Class (Main): G06K-009/00

40/3,K/58 (Item 58 from file: 350)  
DIALOG(R)File 350:Derwent WPIX  
(c) 2005 Thomson Derwent. All rts. reserv.

LATE DATE

013733889 \*\*Image available\*\*  
WPI Acc No: 2001-218119/200122  
XRPX Acc No: N01-155507

Defect analysis using computer imaging for use in production line,  
involves comparing divided sub- images of original image with  
template pattern, to determine defect

Patent Assignee: IMAGING TECHNOLOGY INC (IMAG-N); ISRANI R G (ISRA-I);  
MELIKIAN S H (MELI-I); CORECO IMAGING INC (CORE-N)

Inventor: ISRANI R G; MELIKIAN S H

Number of Countries: 093 Number of Patents: 005

Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week
WO 200077720	A1	20001221	WO 2000US16662	A	20000616	200122 B
AU 200054952	A	20010102	AU 200054952	A	20000616	200122
US 6477275	B1	20021105	US 99333701	A	19990616	200276
US 20030002740	A1	20030102	US 99333701	A	19990616	200305
			US 2002154459	A	20020523	
US 6636634	B2	20031021	US 99333701	A	19990616	200370
			US 2002154459	A	20020523	

Priority Applications (No Type Date): US 99333701 A 19990616; US 2002154459  
A 20020523

Patent Details:

Patent No Kind Lan Pg Main IPC Filing Notes

WO 200077720 A1 E 28 G06K-009/64

Designated States (National): AE AG AL AM AT AU AZ BA BB BG BR BY CA CH  
CN CR CU CZ DE DK DM DZ EE ES FI GB GD GE GH GM HR HU ID IL IN IS JP KE  
KG KP KR KZ LC LK LR LS LT LU LV MA MD MG MK MN MW MX NO NZ PL PT RO RU  
SD SE SG SI SK SL TJ TM TR TT TZ UA UG UZ VN YU ZA ZW

Designated States (Regional): AT BE CH CY DE DK EA ES FI FR GB GH GM GR  
IE IT KE LS LU MC MW MZ NL OA PT SD SE SL SZ TZ UG ZW

AU 200054952 A Based on patent WO 200077720

US 6477275 B1 G06K-009/00

US 20030002740 A1 G06K-009/64 Cont of application US 99333701  
Cont of patent US 6477275

US 6636634 B2 G06K-009/64 Cont of application US 99333701  
Cont of patent US 6477275

Defect analysis using computer imaging for use in production line,  
involves comparing divided sub- images of original image with  
template pattern, to determine defect

Abstract (Basic):

... The original object image is divided into a number of sub-  
images . Each sub- image is compared with a prestored template  
pattern, to generate score signals each representing the location of  
patterns in the image , determined as a function of respective sub-  
images . The score signals are processed using artificial  
intelligence grouping process, to determine the defect.

... a) Defect analysis system ;  
(...)

...b) Defect analysis program...

FIVE  
RELATED  
DOT  
BENEATH

ALL  
LATE  
DATES-

FEEL  
FREE  
TO  
DISREGARD



...For detecting defect in production line e.g. for use in assembly and inspection of electronic components soldered on computer board...

...More accurate representation of the image is enabled by the image sub-dividing process...

...The figure shows the system for locating a pattern within an image .

...Title Terms: ANALYSE ;

International Patent Class (Main): G06K-009/00 ...

... G06K-009/64

International Patent Class (Additional): G06K-005/00 ...

... G06K-009/68 ...

... G06T-007/00 ...

... H04N-007/18

40/3,K/94 (Item 94 from file: 350)  
DIALOG(R) File 350:Derwent WPIX  
(c) 2005 Thomson Derwent. All rts. reserv.

010725173 \*\*Image available\*\*  
WPI Acc No: 1996-222128/199622  
Related WPI Acc No: 1997-145906  
XRAM Acc No: C96-070542  
XRPX Acc No: N96-186377

Computer -assisted method for diagnosing diseases e.g. cancer and osteoporosis - measures concns. of bio-markers, digitises values and introduces them to trained neural network whose output indicates presence or absence of disease

Patent Assignee: HORUS THERAPEUTICS INC (HORU-N)

Inventor: BARNHILL S D; ZHANG Z

Number of Countries: 019 Number of Patents: 002

Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week
WO 9612187	A1	19960425	WO 95US1379	A	19950202	199622 B
AU 9518374	A	19960506	AU 9518374	A	19950202	199636

Priority Applications (No Type Date): US 94323446 A 19941013

Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
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WO 9612187	A1	E	88	G01N-033/53	
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Designated States (National): AU CA JP

Designated States (Regional): AT BE CH DE DK ES FR GB GR IE IT LU MC NL PT SE

AU 9518374	A			G01N-033/53	Based on patent WO 9612187
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Computer -assisted method for diagnosing diseases e.g. cancer and osteoporosis...

...measures concns. of bio-markers, digitises values and introduces them to trained neural network whose output indicates presence or absence of disease

...Abstract (Basic): Diagnosis of disease in a human or animal comprises measuring the concns. of a predetermined set of bio-markers known to be associated with the disease from a biological fluid. The digitised values of the concns. are scaled and introduced to a trained neural network. Output values from the network tend towards an upper value when the disease is present and...

...The method is sensitive and does not expose the patient to unnecessary radiation, e.g. X - rays. The neural network can discern patterns and trends too subtle or complex for humans or computational methods to

Title Terms: COMPUTER0 ;

...International Patent Class (Additional): G06F-159/00

THREE  
RELATED  
DOCS.  
BENEATH

40/3,K/101 (Item 101 from file: 350)  
DIALOG(R)File 350:Derwent WPIX  
(c) 2005 Thomson Derwent. All rts. reserv.

010456985 \*\*Image available\*\*

WPI Acc No: 1995-358304/199546

Related WPI Acc No: 1993-311977

XRPX Acc No: N95-266307

Person identifying system using neural network - matches extracted data feature of input data with recorded data during evaluation by artificial neural network

Patent Assignee: US DEPT OF THE NAVY (USNA )

Inventor: COOPER P; FARSAIE A; KINZER D G

Number of Countries: 001 Number of Patents: 001

Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week
US N8322653	N	19950901	US 9328012	A	19930308	199546 B
			US 94322653	A	19941011	

Priority Applications (No Type Date): US 94322653 A 19941011; US 9328012 A 19930308

Patent Details:

Patent No	Kind	Lan Pg	Main IPC	Filing Notes
US N8322653	N	10	G06K-000/00	CIP of application US 9328012

Person identifying system using neural network - ...

...matches extracted data feature of input data with recorded data during evaluation by artificial neural network

...Abstract (Basic): The system (10) senses person identifying features , extracted from e.g. a photograph , voice pattern, fingerprint and PIN personal identification number. It digitises , preprocesses (14) and stores the acquired data. Sets of numerical values are extracted (16) from the data and processed by the artificial neural network (18) for evaluation .

...The neural network forms a training set to process the extracted data during a training phase. It compares between mass centres and neuron centres adjusted to represent data. Features identifying a person are determined and classified . The neural network provides inputs for the person recognition readout (20) and feedback for the preprocessing and feature extraction. Hence its operation is adjusted in response to variations in the preprocessing and feature extraction...

...USE/ADVANTAGE - For automatic teller machine in bank. Reduced computational complexity as uses artificial neural network -based system so rapid and accurate recognition. Non-algorithmic method to adaptively cluster data on people from few features .

...The system (10) senses person identifying features , extracted from e.g. a photograph , voice pattern, fingerprint and PIN personal identification number. It digitises , preprocesses (14) and stores the acquired data. Sets of numerical values are extracted (16) from the data and processed by the artificial neural network (18) for evaluation .

...

...The neural network forms a training set to process the extracted data during a training phase. It compares between mass centres and neuron centres adjusted to represent data. Features identifying a person are determined and classified. The neural network provides inputs for the person recognition readout (20) and feedback for the preprocessing and feature extraction. Hence its operation is adjusted in response to variations in the preprocessing and feature extraction...

...USE/ADVANTAGE - For automatic teller machine in bank. Reduced computational complexity as uses artificial neural network-based system so rapid and accurate recognition. Non-algorithmic method to adaptively cluster data on people from few features .

...

...The system (10) senses person identifying features , extracted from e.g. a photograph , voice pattern, fingerprint and PIN personal identification number. It digitises , preprocesses (14) and stores the acquired data. Sets of numerical values are extracted (16) from the data and processed by the artificial neural network (18) for evaluation .

...

...The neural network forms a training set to process the extracted data during a training phase. It compares between mass centres and neuron centres adjusted to represent data. Features identifying a person are determined and classified. The neural network provides inputs for the person recognition readout (20) and feedback for the preprocessing and feature extraction. Hence its operation is adjusted in response to variations in the preprocessing and feature extraction...

...USE/ADVANTAGE - For automatic teller machine in bank. Reduced computational complexity as uses artificial neural network-based system so rapid and accurate recognition. Non-algorithmic method to adaptively cluster data on people from few features .

...Title Terms: SYSTEM ;  
International Patent Class (Main): G06K-000/00

40/3,K/104 (Item 104 from file: 350)  
DIALOG(R) File 350:Derwent WPIX  
(c) 2005 Thomson Derwent. All rts. reserv.

010199553 \*\*Image available\*\*  
WPI Acc No: 1995-100807/199514  
XRPX Acc No: N96-088966

Micro-calcification detecting method used in diagnosing cancer -  
involves converting interested area of digital breast X - ray image  
into digital data and inputting data in neural network NoAbstract

Patent Assignee: ARCH DEV CORP (ARCH-N)

Inventor: DOI K; ZHANG W

Number of Countries: 002 Number of Patents: 002

Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week
JP 6343627	A	19941220	JP 9497365	A	19940511	199514 B
US 5491627	A	19960213	US 9360531	A	19930513	199612

Priority Applications (No Type Date): US 9360531 A 19930513

Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
JP 6343627	A		25		
US 5491627	A		30		

Micro-calcification detecting method used in diagnosing cancer...  
...involves converting interested area of digital breast X - ray image  
into digital data and inputting data in neural network NoAbstract

...Abstract (Basic): The method involves obtaining a digital mammogram  
and...

...extracting regions of interest from the mammogram suspected of  
containing a microcalcification. Regions of interest are converted  
into corresponding numerical data . The numerical data is input into a  
shift-invariant neural network trained to detect  
microcalcifications for processing. The neural network produces  
corresponding output images .

...A microcalcification in the digital mammogram is detected using  
the output images . Extracting the regions of interest involves  
extracting regions suspected of containing a clustered  
microcalcification. This in turn involves selecting regions containing  
false-positive microcalcifications . Processing by the neural  
network includes removing a portion of the false-positive  
microcalcifications selected in the extracting step...

...ADVANTAGE - Preserves true positive detections while lowering false  
ones. Uses regions of interest in the spatial domain to perform  
clustered microcalcification. Performs microcalcification detection  
independently of relative locations of microcalcifications and cluster  
orientation. Uses shift invariant neural network and feature  
extraction techniques to detect microcalcifications. Uses feature  
thresholding in addition to neural network to remove false  
positives

...Title Terms: DETECT ;

RELATED  
Do C.  
BENTATH

40/3,K/108 (Item 108 from file: 350)  
DIALOG(R)File 350:Derwent WPIX  
(c) 2005 Thomson Derwent. All rts. reserv.

010067117 \*\*Image available\*\*  
WPI Acc No: 1994-334830/199442  
XRPX Acc No: N94-262934

Computer implemented process of recognising image pattern among set of known templates - involves scanning image, segmenting image to detect pattern, preprocessing detected pattern and applying preprocessed detected pattern to trained neural network

Patent Assignee: CANON KK (CANO )  
Inventor: AVI-ITZHAK H I; DIEP T A; GARLAND H T; THAN A D  
Number of Countries: 005 Number of Patents: 006  
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week
EP 622750	A2	19941102	EP 94303081	A	19940428	199442 B
EP 622750	A3	19950426	EP 94303081	A	19940428	199545
US 5475768	A	19951212	US 9355523	A	19930429	199604
US 5625707	A	19970429	US 9355523	A	19930429	199723
			US 95445470	A	19950522	
EP 622750	B1	20000105	EP 94303081	A	19940428	200006
DE 69422446	E	20000210	DE 622446	A	19940428	200015
			EP 94303081	A	19940428	

Priority Applications (No Type Date): US 9355523 A 19930429; US 95445470 A 19950522

Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
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EP 622750	A2	E	12	G06K-009/36	
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Designated States (Regional): DE FR GB IT

EP 622750	B1	E		G06K-009/36	
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Designated States (Regional): DE FR GB IT

DE 69422446	E			G06K-009/36	Based on patent EP 622750
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US 5475768	A		11	G06K-009/66	
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US 5625707	A		11	G06T-001/40	Div ex application US 9355523
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Div ex patent US 5475768

EP 622750	A3			G06K-009/36	
-----------	----	--	--	-------------	--

Computer implemented process of recognising image pattern among set of known templates - ...

...involves scanning image, segmenting image to detect pattern, preprocessing detected pattern and applying preprocessed detected pattern to trained neural network

...Abstract (Basic): The process involves scanning an image including a pattern to be recognised and detecting the pattern by segmenting the image. A neural network (108) is trained using the set of known templates. The detected pattern is preprocessed and the preprocessed pattern is applied to the trained neural network as input. The pattern is recognised as one of the known templates corresp. to an output of the trained neural network.

...

...The detected pattern is comprised of a number of pixels.

Preprocessing involves filtering pixel values by selectively assigning a predetermined filtered pixel value to a subset...

...ADVANTAGE - Neural network based OCR system has high accuracy even for imperfect images.

TWO  
RELATED  
DOCS,  
BENEATH

...Abstract (Equivalent): A computer -implemented process of training a neural network , said process comprising...

...a) providing a plurality of templates , each template corresponding to a distinct image ; and...

...b) for each of the plurality of templates :

...  
...defining a frame around the template ;  
...

...determining a centroid of the template ;  
...

...positioning the template within the frame such that the centroid is centrally located with respect to the frame...

...randomly displacing the template horizontally and vertically within the frame; and...

... training the neural network by applying the randomly displaced template to the neural network .  
...

...A computer -implemented process of recognizing a pattern in an image among a set of known templates , the process comprising...

...a) training a neural network using said set of known templates ;  
...

...b) scanning said image ; c) detecting said pattern by segmenting said scanned image into a detected pattern comprising a plurality of pixels, each such pixel having a value; d) preprocessing said detected pattern by: i) determining a minimum of said values of said pixels; ii) subtracting the...

...of said pixels in said subset not exceeding a threshold value; and e) recognizing said preprocessed detected pattern as corresponding to one of said known templates by applying said preprocessed detected pattern to said trained neural network .

Title Terms: COMPUTER ;

International Patent Class (Main): G06K-009/36 ...

... G06K-009/66 ...

... G06T-001/40

40/3,K/119 (Item 119 from file: 350)  
DIALOG(R)File 350:Derwent WPIX  
(c) 2005 Thomson Derwent. All rts. reserv.

009618428 \*\*Image available\*\*  
WPI Acc No: 1993-311977/199339  
Related WPI Acc No: 1995-358304  
XRPX Acc No: N93-240197

Feature extraction technique for target recognition - sensing image scene from different viewing angles for image data acquisition, extracting features from data, and evaluating data in artificial neural network to identify target within image scene

Patent Assignee: US DEPT OF THE NAVY (USNA )

Inventor: FARSAIE A; FULLER J J

Number of Countries: 001 Number of Patents: 001

Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week
US N8028012	N	19930915	US 9328012	A	19930308	199339 B

Priority Applications (No Type Date): US 9328012 A 19930308

Patent Details:

Patent No	Kind	Lan Pg	Main IPC	Filing Notes
-----------	------	--------	----------	--------------

US N8028012	N	10	G06F-000/00	
-------------	---	----	-------------	--

Feature extraction technique for target recognition...  
...sensing image scene from different viewing angles for image data acquisition, extracting features from data, and evaluating data in artificial neural network to identify target within image scene

...Abstract (Basic): method involves gathering input data relating to baseline targets within real environments, often having an image degrading characteristic, during an image acquisition phase (12). The gathered image data is then digitised and pre-processed (14) to eliminate extraneous data. Extraction of target features from such pre-processed image data is performed by feature extraction (16...)

...The extracted feature data then undergoes training or testing procedures through an artificial neural network (18) in order to provide inputs for target recognition readout (20). The output of the artificial neural network also provides feedbacks for preprocessing and feature extraction. Operation of the artificial neural network is thereby adjusted in response to variations in the preprocessing of the input image data and feature extraction...

...ADVANTAGE - Reduces training time and computational complexity in artificial neural network system. Rapid and accurate recognition and identification of image features extracted from input image data...

...method involves gathering input data relating to baseline targets within real environments, often having an image degrading characteristic, during an image acquisition phase (12). The gathered image data is then digitised and pre-processed (14) to eliminate extraneous data. Extraction of target features from such pre-processed image data is performed by feature extraction (16...)

...The extracted feature data then undergoes training or testing procedures through an artificial neural network (18) in order to provide inputs for target recognition readout (20). The output of the



artificial neural network also provides feedbacks for preprocessing and feature extraction. Operation of the artificial neural network is thereby adjusted in response to variations in the preprocessing of the input image data and feature extraction...

...ADVANTAGE - Reduces training time and computational complexity in artificial neural network system. Rapid and accurate recognition and identification of image features extracted from input image data...

...method involves gathering input data relating to baseline targets within real environments, often having an image degrading characteristic, during an image acquisition phase (12). The gathered image data is then digitised and pre-processed (14) to eliminate extraneous data. Extraction of target features from such pre-processed image data is performed by feature extraction (16...

...The extracted feature data then undergoes training or testing procedures through an artificial neural network (18) in order to provide inputs for target recognition readout (20). The output of the artificial neural network also provides feedbacks for preprocessing and feature extraction. Operation of the artificial neural network is thereby adjusted in response to variations in the preprocessing of the input image data and feature extraction...

...ADVANTAGE - Reduces training time and computational complexity in artificial neural network system. Rapid and accurate recognition and identification of image features extracted from input image data...

Title Terms: FEATURE ;

International Patent Class (Main): G06F-000/00

40/3,K/169 (Item 169 from file: 347)  
DIALOG(R)File 347:JAPIO  
(c) 2005 JPO & JAPIO. All rts. reserv.

04780729 \*\*Image available\*\*  
METHOD AND DEVICE FOR PROCESSING IMAGE

PUB. NO.: 07-073329 [JP 7073329 A]  
PUBLISHED: March 17, 1995 (19950317)  
INVENTOR(s): TAN EE DEIEPU  
HADAARU AI ABUIIITSUAAKU  
HARII TEII GAARANDO  
APPLICANT(s): CANON INC [000100] (A Japanese Company or Corporation), JP  
(Japan)  
APPL. NO.: 06-092540 [JP 9492540]  
FILED: April 28, 1994 (19940428)  
PRIORITY: 7-55,523 [US 55523-1993], US (United States of America),  
April 29, 1993 (19930429)

METHOD AND DEVICE FOR PROCESSING IMAGE

INTL CLASS: G06T-007/00 ; G06T-007/60 ; G06K-009/62  
...JAPIO CLASS: Input Output Units)  
...JAPIO KEYWORD:Microcomputers & Microprocessors )

ABSTRACT

PURPOSE: To accurately recognize a pattern from the image having much noise by learning a neural network while using a known template pattern, performing the preprocessing of a detected pattern, and applying the preprocessed pattern to the neural network .

...

...CONSTITUTION: A neural network 108 is learnt by using the known template pattern. A scanner 102 is used for providing the two-dimensional arrangement of picture elements expressing a scanning image containing the pattern of a recognizing target. A segment 104 is detected by separating this pattern from the other image elements. A processor 106 performs the preprocessing of the detected pattern for facilitating pattern recognition. The neural network 108 receives the detected preprocessed pattern as an input and outputs a signal for expressing the recognized pattern. This preprocessing is composed of deciding the centroid of the pattern and positioning the centroid at the

THREE  
RELATED  
DOCS,  
BENEATH

40/3,K/219 (Item 219 from file: 347)  
DIALOG(R)File 347:JAPIO  
(c) 2005 JPO & JAPIO. All rts. reserv.

03566478 \*\*Image available\*\*  
IMAGE SORTING/IDENTIFYING DEVICE

PUB. NO.: 03-229378 [JP 3229378 A]  
PUBLISHED: October 11, 1991 (19911011)  
INVENTOR(s): ISO TOSHIKI  
KOSUGI MAKOTO  
APPLICANT(s): NIPPON TELEGR & TELEPH CORP <NTT> [000422] (A Japanese  
Company or Corporation), JP (Japan)  
APPL. NO.: 02-025699 [JP 9025699]  
FILED: February 05, 1990 (19900205)  
JOURNAL: Section: P, Section No. 1296, Vol. 16, No. 9, Pg. 105,  
January 10, 1992 (19920110)

IMAGE SORTING/IDENTIFYING DEVICE

INTL CLASS: G06F-015/70 ; G06F-015/18  
...JAPIO CLASS: Computer Applications)

#### ABSTRACT

PURPOSE: To sort and identify even the unknown **images** by combining the **neural networks** having the **learning** functions and capable of the nonlinear mapping in parallel to each other and in a...

...CONSTITUTION: A face **image** data input part 1 fetches the unknown face **image** data and sends this data to a **pre - processing** circuit 2. This circuit 2 extracts the **features** of each parts out of the face **image** data, i.e., the **output** of the part 1 and at the same time sorts the parts with the function which is previously **learnt** from various face **image** data. The **outputs** of these circuits 2 are collected in a main **neural network** 3 where the face **images** are sorted and identified by the function which is also previously **learnt** . Thus even the unknown face **images** can be sorted and identified.

Set	Items	Description
S1	606387	IMAGE? OR IMAGING? OR GRAPHIC? OR VIDEO? OR BITMAP? OR BIT- ( ) (MAP OR MAPS OR MAPPED OR MAPPING)
S2	342282	SONOGRAM? OR VISUAL? OR ULTRASOUND? OR ULTRASONIC? OR PICTO- RIAL? OR XRAY? OR X( ) (RAY OR RAYS OR RAYED OR RAYING) OR RADI- OGRA?
S3	108298	PHOTOGRAPH? OR PET(2N)SCAN? OR PETSCAN? OR POSITRON( )EMISS- ION? OR MAGNETIC( )RESONANC? OR MRI
S4	15657	TOMOGRAPH? OR MAMMOGRAM? OR CATSCAN? OR (CAT OR CT) ( )SCAN? - OR CTSCAN?
S5	516244	COMPUTER? OR DIGITAL? OR DIGITIZ? OR DIGITIS? OR BINARY?
S6	171956	DATAPROCESS? OR MICROPROCESS? OR CENTRALPROCESS? OR (MICRO OR DATA OR CENTRAL) ( )PROCESS?
S7	105910	PROCESS?(2N) (MODULE? OR UNIT?)
S8	1599	SVM OR SUPPORT( )VECTOR? OR VECTOR( )MACHINE?
S9	12510	MACHINE?(2N)LEARN? OR MACHINE( )VECTOR? OR NEURAL( )NETWORK? OR ARTIFICIAL( ) (NEURAL? OR INTELLIGEN?) OR BACK( )PROPAGAT? OR OPTIM?( ) (HYPERPLAN? OR HYPER( )PLAN?) OR CYBERNET?
S10	68366	PREPROCESS? OR PREANALY? OR PREEXAMIN? OR PREPARS? OR (BEF- ORE? OR PRIOR? OR PRELIMIN? OR PREPARAT?) (2W)PROCESS?
S11	108252	IDENTIF?(3N) (MISSING? OR ERROR? OR ERRONEOUS? OR FLAW?) OR TRANSCOD? OR DATA(3N) (MODIF? OR CONVERT? OR CONVERSION? OR AL- TER? OR CHANGE? OR CHANGING)
S12	10407	TRANSFORM? ?(3N) (RADON OR HOUGH) OR PRECLASSIF? OR PRE( ) (P- ROCESS? OR ANALY? OR EXAMIN? OR PARS? OR CLASSIF?)
S13	456274	TRAIN? OR LEARN? OR EDUCAT? OR INSTRUCT? OR TEACH? OR TAUG- HT? OR DIDACT? OR SELFTEACH? OR AUTODIDACT?
S14	981173	ANALYS? OR ANALYZ? OR TEST??? OR DETECT?
S15	886381	MONITOR? OR GAUG? OR RATE? OR RATING? OR SAMPLE? OR SAMPLI- NG?
S16	1837109	EXAMIN? OR EVALUAT? OR ASCERTAIN? OR ASSESS?
S17	1780715	KNOWN? OR TEMPLAT? OR STENCIL? OR STANDARD? ? OR NORM? ? OR PAR OR PROFILE?
S18	967103	CONTROL OR CRITER? OR TOUCHSTONE? OR BENCHMARK? OR YARDSTI- CK? OR IDEAL? ? OR PARAGON? ?
S19	1600114	CLASSIF? OR SUBCLASSIF? OR SYSTEM? OR SUBSYSTEM? OR FEATUR- E? OR SUBFEATUR? OR CHARACTERISTIC? OR SUBCHARACTERISTIC?
S20	1086021	ATTRIBUT? OR SUBATTRIBUT? OR SEGMENT? OR SUBSEGMENT? OR CL- ASS?? OR SUBCLASS?? OR SECTION? OR SUBSECTION?
S21	429565	INDEX? OR SUBINDEX? OR CATEGOR? OR SUBCATEGOR? OR SUBDIVI? OR DIVISION?
S22	1491745	SET OR SETS OR RESULT? OR OUTPUT? OR PROCESS?( )DATA
S23	579576	REALTIME? OR REAL( )TIME? OR RTOS OR SYNCHRON? OR SIMULTAN? OR CONTEMPORAN? OR LIVE
S24	235455	IC=(G06F? OR G06E? OR G06K? OR G06T? OR H04N?)
S25	2399	S1:S4(10N)S5:S7 AND S1:S7(20N)S8:S9
S26	787	S25 AND S10:S12(20N)S1:S7
S27	705	S26 AND S13 AND S14:S16
S28	703	S27 AND S13:S16(10N)S17:S22
S29	670	S28 AND S23:S24
S30	701	S28 AND S17:S18 AND S19:S21 AND S22
S31	668	S29 AND S30
S32	362	S31 AND S8:S9(10N)S13
S33	457	S31 AND S13(5N) (S22 OR DATA?) AND S14:S16(5N) (S22 OR DATA?)
S34	565	S31 AND S17:S18(5N) (S22 OR DATA?)
S35	411	S26:S31 AND S1:S4(5N)S5:S7(5N)S14:S16
S36	119	S35 AND S32 AND S33 AND S34
S37	336	S35 AND S32:S34
S38	234	S37 AND S24
S39	173	S37:S38 AND S1:S12/TI

? show files

File 348:EUROPEAN PATENTS 1978-2005/May W03

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File 349:PCT FULLTEXT 1979-2005/UB=20050519,UT=20050512

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?

36/3/27 (Item 27 from file: 348)  
DIALOG(R) File 348:EUROPEAN PATENTS  
(c) 2005 European Patent Office. All rts. reserv.

00626757

**Application of neural networks as an aid in medical diagnosis and general anomaly detection.**

**Anwendung von Neuralnetzwerken als Hilfe für die medizinische Diagnose und allgemeiner Nachweis von Anomalien.**

**Application de reseaux neuronaux pour aider dans le diagnostic medical et detection generale d'anomalies.**

PATENT ASSIGNEE:

E.I. DU PONT DE NEMOURS AND COMPANY, (200580), 1007 Market Street,  
Wilmington Delaware 19898, (US), (applicant designated states:  
BE;DE;FR;GB)

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LEGAL REPRESENTATIVE:

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, (DE)

PATENT (CC, No, Kind, Date): EP 610805 A2 940817 (Basic)  
EP 610805 A3 950607

APPLICATION (CC, No, Date): EP 94101600 940203;

PRIORITY (CC, No, Date): US 16343 930211

DESIGNATED STATES: BE; DE; FR; GB

INTERNATIONAL PATENT CLASS: G06F-015/80 ; G06F-019/00

ABSTRACT WORD COUNT: 93

LANGUAGE (Publication,Procedural,Application): English; English; English

FULLTEXT AVAILABILITY:

Available Text	Language	Update	Word Count
CLAIMS A	(English)	EPABF2	450
SPEC A	(English)	EPABF2	4645
Total word count - document A			5095
Total word count - document B			0
Total word count - documents A + B			5095

*Two  
RELATED  
DOX  
BENEATH*

36/3/113 (Item 78 from file: 349)  
DIALOG(R) File 349:PCT FULLTEXT  
(c) 2005 WIPO/Univentio. All rts. reserv.

00365227

COMPUTER ASSISTED METHODS FOR DIAGNOSING DISEASES  
PROCEDES DE DIAGNOSTIC DE MALADIES ASSISTE PAR ORDINATEUR

Patent Applicant/Assignee:

HORUS THERAPEUTICS INC,

Inventor(s):

BARNHILL Stephen M,

ZHANG Zhen,

Patent and Priority Information (Country, Number, Date):

Patent: WO 9705553 A1 19970213

Application: WO 96US12177 19960725 (PCT/WO US9612177)

Priority Application: US 951425 19950725; US 96642848 19960503

Designated States:

(Protection type is "patent" unless otherwise stated - for applications prior to 2004)

AU CA CN JP NZ AT BE CH DE DK ES FI FR GB GR IE IT LU MC NL PT SE

Publication Language: English

Fulltext Word Count: 16562

THREE  
RELATED  
DOX  
BENEATH

39/3/56 (Item 56 from file: 348)  
DIALOG(R) File 348:EUROPEAN PATENTS  
(c) 2005 European Patent Office. All rts. reserv.

00473856

Computer-aided diagnosis system for medical use

Rechnergestutztes System zur Diagnose fur medizinischen Gebrauch

Systeme assiste par ordinateur pour le diagnostic a usage medical

PATENT ASSIGNEE:

KABUSHIKI KAISHA TOSHIBA, (213130), 72, Horikawa-cho, Saiwai-ku,  
Kawasaki-shi, Kanagawa-ken 210-8572, (JP), (Proprietor designated  
states: all)

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Komatsu, Kenichi, c/o Intellectual Property Div., Kabushiki Kaisha  
Toshiba, 1-1 Shibaura 1-chome, Minato-ku, Tokyo 105, (JP)

Ema, Takehiro, c/o Intellectual Property Div., Kabushiki Kaisha Toshiba,  
1-1 Shibaura 1-chome, Minato-ku, Tokyo 105, (JP)

LEGAL REPRESENTATIVE:

Blumbach, Kramer & Partner GbR (101302), Radeckestrasse 43, 81245 Munchen  
, (DE)

PATENT (CC, No, Kind, Date): EP 487110 A2 920527 (Basic)  
EP 487110 A3 930929  
EP 487110 B1 991006

APPLICATION (CC, No, Date): EP 91119983 911122;

PRIORITY (CC, No, Date): JP 90320498 901122

DESIGNATED STATES: DE; NL

INTERNATIONAL PATENT CLASS: G06F-019/00

ABSTRACT WORD COUNT: 197

NOTE:

Figure number on first page: 1

LANGUAGE (Publication,Procedural,Application): English; English; English

FULLTEXT AVAILABILITY:

Available Text	Language	Update	Word Count
CLAIMS B	(English)	9940	586
CLAIMS B	(German)	9940	589
CLAIMS B	(French)	9940	715
SPEC B	(English)	9940	13386
Total word count - document A			0
Total word count - document B			15276
Total word count - documents A + B			15276

FIVE  
RELATED  
DOCS.  
BENEATH



39/3/60 (Item 60 from file: 348)  
DIALOG(R) File 348:EUROPEAN PATENTS  
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00352006

Method and apparatus for adaptive learning type general purpose image  
measurement and recognition

Verfahren und Gerat fur universelle adaptiv lernende Bildmessung und  
-erkennung

Procede et dispositif de mesure et reconnaissance d' images universelles  
avec apprentissage adaptatif

PATENT ASSIGNEE:

KABUSHIKI KAISHA OUYO KEISOKU KENKYUSHO, (807871), 3-26-12, Kita-Senzoku,  
Ohta-ku, Tokyo, (JP), (applicant designated states: DE;FR;GB;IT;SE)  
AGENCY OF INDUSTRIAL SCIENCE AND TECHNOLOGY, (213421), 3-1, Kasumigaseki  
1-chome, Chiyoda-ku Tokyo, (JP), (applicant designated states:  
DE;FR;GB;IT;SE)

INVENTOR:

Otsu, Nobuyuki, 1-1-4, Umezono, Tsukuba-Shi Ibaraki, (JP)  
Kurita, Takio, 1-1-4, Umezono, Tsukuba-Shi Ibaraki, (JP)  
Kuwashima, Shigesumi, 3-22-3, Kita-Senzoku Ohta-ku, Tokyo, (JP)

LEGAL REPRESENTATIVE:

Klunker . Schmitt-Nilson . Hirsch (101001), Winzererstrasse 106, 80797  
Munchen, (DE)

PATENT (CC, No, Kind, Date): EP 363828 A2 900418 (Basic)  
EP 363828 A3 920812  
EP 363828 B1 990107

APPLICATION (CC, No, Date): EP 89118529 891005;

PRIORITY (CC, No, Date): JP 88255678 881011; JP 88255679 881011

DESIGNATED STATES: DE; FR; GB; IT; SE

INTERNATIONAL PATENT CLASS: G06K-009/52 ; G06K-009/62B

ABSTRACT WORD COUNT: 206

LANGUAGE (Publication,Procedural,Application): English; English; English  
FULLTEXT AVAILABILITY:

Available Text	Language	Update	Word Count
CLAIMS B	(English)	9901	679
CLAIMS B	(German)	9901	612
CLAIMS B	(French)	9901	726
SPEC B	(English)	9901	6260
Total word count - document A			0
Total word count - document B			8277
Total word count - documents A + B			8277

Two  
related  
BOX  
BENEATH

39/3/140 (Item 78 from file: 349)  
DIALOG(R)File 349:PCT FULLTEXT  
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00549760 \*\*Image available\*\*

METHOD AND SYSTEM FOR THE COMPUTERIZED ANALYSIS OF BONE MASS AND STRUCTURE  
PROCEDE ET SYSTEME D'ANALYSE INFORMATISES DE LA MASSE ET DE LA STRUCTURE DE  
L'OS

Patent Applicant/Assignee:

ARCH DEVELOPMENT CORPORATION,

Inventor(s):

JIANG Chunsheng,

CHINANDER Michael R,

GIGER Maryellen L,

Patent and Priority Information (Country, Number, Date):

Patent: WO 200013133 A1 20000309 (WO 0013133)

Application: WO 99US18825 19990827 (PCT/WO US9918825)

Priority Application: US 98141535 19980828

Designated States:

(Protection type is "patent" unless otherwise stated - for applications  
prior to 2004)

AU CA JP AT BE CH CY DE DK ES FI FR GB GR IE IT LU MC NL PT SE

Publication Language: English

Fulltext Word Count: 19330

*Two  
related  
DOX.  
BENEATH*

39/3/142 (Item 80 from file: 349)  
DIALOG(R) File 349:PCT FULLTEXT  
(c) 2005 WIPO/Univentio. All rts. reserv.

00497502 \*\*Image available\*\*

METHOD AND SYSTEM FOR AUTOMATED MULTI-SAMPLED DETECTION OF LESIONS IN  
IMAGES

PROCEDE ET SYSTEME PERMETTANT DE DETECTER AUTOMATIQUEMENT AVEC PLUSIEURS  
ECHANTILLONS DES LESIONS DANS LES IMAGES

Patent Applicant/Assignee:

ARCH DEVELOPMENT CORPORATION,

Inventor(s):

NISHIKAWA Robert M,

DOI Kunio,

Patent and Priority Information (Country, Number, Date):

Patent: WO 9928854 A1 19990610

Application: WO 98US24932 19981125 (PCT/WO US9824932)

Priority Application: US 97979639 19971128

Designated States:

(Protection type is "patent" unless otherwise stated - for applications  
prior to 2004)

AU CA JP AT BE CH CY DE DK ES FI FR GB GR IE IT LU MC NL PT SE

Publication Language: English

Fulltext Word Count: 7564

*HAVE  
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DOCS  
BRIEFING*

39/3/147 (Item 85 from file: 349)  
DIALOG(R)File 349:PCT FULLTEXT  
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00473338 \*\*Image available\*\*  
METHOD AND SYSTEM FOR THE AUTOMATED ANALYSIS OF LESIONS IN MAGNETIC  
RESONANCE IMAGES  
PROCEDE ET SYSTEME D'ANALYSE AUTOMATIQUE DE LESIONS DANS DES IMAGES  
OBTENUES PAR RESONANCE MAGNETIQUE  
Patent Applicant/Assignee:  
ARCH DEVELOPMENT CORPORATION,  
Inventor(s):  
GILHUIJS Kenneth,  
GIGER Maryellen L,  
BICK Ulrich,  
Patent and Priority Information (Country, Number, Date):  
Patent: WO 9904690 A1 19990204  
Application: WO 98US15165 19980724 (PCT/WO US9815165)  
Priority Application: US 97900188 19970725  
Designated States:  
(Protection type is "patent" unless otherwise stated - for applications  
prior to 2004)  
AU CA JP AT BE CH CY DE DK ES FI FR GB GR IE IT LU MC NL PT SE  
Publication Language: English  
Fulltext Word Count: 9223

FIVE  
RELATED  
DOCS,  
BENEATH

39/3/149 (Item 87 from file: 349)  
DIALOG(R)File 349:PCT FULLTEXT  
(c) 2005 WIPO/Univentio. All rts. reserv.

00452737 \*\*Image available\*\*

METHOD AND APPARATUS FOR AUTOMATIC MUSCLE SEGMENTATION IN DIGITAL  
MAMMOGRAMS

PROCEDE ET APPAREIL DE SEGMENTATION AUTOMATIQUE DU TISSU MUSCULAIRE DANS  
LES CLICHES MAMMAIRES NUMERIQUES

Patent Applicant/Assignee:

R2 TECHNOLOGY INC,

Inventor(s):

KARSSEMEIJER Nico,

Patent and Priority Information (Country, Number, Date):

Patent: WO 9843201 A1 19981001

Application: WO 98US6207 19980327 (PCT/WO US9806207)

Priority Application: US 97825291 19970327

Designated States:

(Protection type is "patent" unless otherwise stated - for applications  
prior to 2004)

AL AM AU AZ BA BB BG BR BY CA CN CU CZ EE GE GH GW HU ID IL IS JP KG KP  
KR KZ LC LK LR LT LV MD MG MK MN MX NO NZ PL RO RU SG SI SK SL TJ TM TR  
TT UA UZ VN YU GH GM KE LS MW SD SZ UG ZW AM AZ BY KG KZ MD RU TJ TM AT  
BE CH DE DK ES FI FR GB GR IE IT LU MC NL PT SE BF BJ CF CG CI CM GA GN  
ML MR NE SN TD TG

Publication Language: English

Fulltext Word Count: 7427

FOUR  
RELATED  
DOCS.  
BENEATH

39/3/155 (Item 93 from file: 349)  
DIALOG(R) File 349:PCT FULLTEXT  
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00388694 \*\*Image available\*\*

METHOD AND APPARATUS FOR TRAINING A NEURAL NETWORK TO DETECT AND CLASSIFY  
OBJECTS WITH UNCERTAIN TRAINING DATA

PROCEDE ET APPAREIL DE FORMATION D'UN RESEAU NEURONAL A LA DETECTION ET LA  
CLASSIFICATION D'OBJETS AVEC DES DONNEES DE FORMATION INCERTAINES

Patent Applicant/Assignee:

SARNOFF CORPORATION,

Inventor(s):

SPENCE Clay Douglas,

PEARSON John Carr,

SAJDA Paul,

Patent and Priority Information (Country, Number, Date):

Patent: WO 9729437 A1 19970814

Application: WO 97US2216 19970207 (PCT/WO US9702216)

Priority Application: US 9611434 19960209

Designated States:

(Protection type is "patent" unless otherwise stated - for applications  
prior to 2004)

CA JP KR MX AT BE CH DE DK ES FI FR GB GR IE IT LU MC NL PT SE

Publication Language: English

Fulltext Word Count: 9976

THREE  
RELATED  
DOCS.  
BENEATH

39/3/164 (Item 102 from file: 349)  
DIALOG(R)File 349:PCT FULLTEXT  
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00315897 \*\*Image available\*\*

NEURAL NETWORK FOR CELL IMAGE ANALYSIS FOR IDENTIFICATION OF ABNORMAL CELLS  
RESEAU NEURONAL DESTINE A L'ANALYSE D'UNE IMAGE DE CELLULES AUX FINS  
D'IDENTIFICATION DE CELLULES ANORMALES

Patent Applicant/Assignee:

UROCOR INC,

Inventor(s):

VELTRI Robert W,

ASHENAYI Kaveh,

HU Ying,

O'DOWD Gerard J,

Patent and Priority Information (Country, Number, Date):

Patent: WO 9534050 A1 19951214

Application: WO 95US7005 19950601 (PCT/WO US9507005)

Priority Application: US 94253933 19940603

Designated States:

(Protection type is "patent" unless otherwise stated - for applications  
prior to 2004)

AU CA JP AT BE CH DE DK ES FR GB GR IE IT LU MC NL PT SE

Publication Language: English

Fulltext Word Count: 25312

*TWO  
RELATED  
DOCS.  
BENFATH*

Set	Items	Description
S1	4224037	IMAGE? OR IMAGING? OR GRAPHIC? OR VIDEO? OR BITMAP? OR BIT- ( ) (MAP OR MAPS OR MAPPED OR MAPPING)
S2	5271882	SONOGRA? OR VISUAL? OR ULTRASOUND? OR ULTRASONIC? OR PICTO- RIAL? OR XRAY? OR X( ) (RAY OR RAYS OR RAYED OR RAYING) OR RADIO- OGRA?
S3	1573623	PHOTOGRAPH? OR PET(2N)SCAN? OR PETSCAN? OR POSITRON( ) EMISS- ION? OR MAGNETIC( ) RESONANC? OR MRI
S4	1063560	TOMOGRAPH? OR MAMMOGRA? OR CATSCAN? OR (CAT OR CT) ( ) SCAN? - OR CTSCAN?
S5	6881368	COMPUTER? OR DIGITAL? OR DIGITIZ? OR DIGITIS? OR BINARY?
S6	579887	DATAPROCESS? OR MICROPROCESS? OR CENTRALPROCESS? OR (MICRO OR DATA OR CENTRAL) ( ) PROCESS?
S7	54213	PROCESS?(2N) (MODULE? OR UNIT?)
S8	15892	SVM OR SUPPORT( ) VECTOR? OR VECTOR( ) MACHINE?
S9	691575	MACHINE?(2N) LEARN? OR MACHINE( ) VECTOR? OR NEURAL( ) NETWORK? OR ARTIFICIAL( ) (NEURAL? OR INTELLIGEN?) OR BACK( ) PROPAGAT? OR OPTIM?( ) (HYPERPLAN? OR HYPER( ) PLAN?) OR CYBERNET?
S10	71273	PREPROCESS? OR PREANALY? OR PREEXAMIN? OR PREPARS? OR (BEF- ORE? OR PRIOR? OR PRELIMIN? OR PREPARAT?) (2W) PROCESS?
S11	147054	IDENTIF?(3N) (MISSING? OR ERROR? OR ERRONEOUS? OR FLAW?) OR TRANSCOD? OR DATA(3N) (MODIF? OR CONVERT? OR CONVERSION? OR AL- TER? OR CHANGE? OR CHANGING)
S12	31322	TRANSFORM? ?(3N) (RADON OR HOUGH) OR PRECLASSIF? OR PRE( ) (P- ROCESS? OR ANALY? OR EXAMIN? OR PARS? OR CLASSIF?)
S13	3672601	TRAIN? OR LEARN? OR EDUCAT? OR INSTRUCT? OR TEACH? OR TAUG- HT? OR DIDACT? OR SELFTEACH? OR AUTODIDACT?
S14	1026	S1:S4 AND S5:S7 AND S8:S9 AND S10:S12 AND S13
S15	730	S14 AND PY<2000
S16	334	S15 AND S1:S4(5N)S5:S7
S17	152	S16 AND S1:S4(5N)S10:S12
S18	176	S16 AND S1:S4(5N)S8:S9
S19	90	S17 AND S18
S20	75	RD (unique items)
? show files		
File	2:INSPEC 1969-2005/May W4	(c) 2005 Institution of Electrical Engineers
File	6:NTIS 1964-2005/May W4	(c) 2005 NTIS, Intl Cpyrght All Rights Res
File	8:Ei Compendex(R) 1970-2005/May W3	(c) 2005 Elsevier Eng. Info. Inc.
File	34:SciSearch(R) Cited Ref Sci 1990-2005/May W5	(c) 2005 Inst for Sci Info
File	35:Dissertation Abs Online 1861-2005/May	(c) 2005 ProQuest Info&Learning
File	62:SPIN(R) 1975-2005/Mar W3	(c) 2005 American Institute of Physics
File	65:Inside Conferences 1993-2005/May W5	(c) 2005 BLDSC all rts. reserv.
File	73:EMBASE 1974-2005/May W4	(c) 2005 Elsevier Science B.V.
File	94:JICST-EPlus 1985-2005/Apr W2	(c) 2005 Japan Science and Tech Corp(JST)
File	95:TEME-Technology & Management 1989-2005/Apr W4	(c) 2005 FIZ TECHNIK
File	99:Wilson Appl. Sci & Tech Abs 1983-2005/Apr	(c) 2005 The HW Wilson Co.
File	111:TGG Natl.Newspaper Index(SM) 1979-2005/May 31	(c) 2005 The Gale Group
File	144:Pascal 1973-2005/May W4	(c) 2005 INIST/CNRS



File 155:MEDLINE(R) 1951-2005/May W5

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File 256:TecInfoSource 82-2005/Apr

(c) 2005 Info.Sources Inc

File 434:SciSearch(R) Cited Ref Sci 1974-1989/Dec

(c) 1998 Inst for Sci Info

?

20/3,K/9 (Item 9 from file: 2)

DIALOG(R)File 2:INSPEC

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4868241 INSPEC Abstract Number: A9504-8760J-031, C9503-7330-050

Title: Automatic segmentation of liver structure in CT images using a neural network

Author(s): Tsai, D.-Y.

Author Affiliation: Gifu Nat. Coll. of Technol., Japan

Journal: IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences vol.E77-A, no.11 p.1892-5

Publication Date: Nov. 1994 Country of Publication: Japan

CODEN: IFSEEX ISSN: 0916-8508

Language: English

Subfile: A C

Copyright 1995, IEE

Title: Automatic segmentation of liver structure in CT images using a neural network

Abstract: Describes a segmentation method of liver structure from abdominal CT images using a three-layered neural network (NN). Before the NN segmentation, preprocessing is employed to locally enhance the contrast of the region of interest. Postprocessing is also...

... the proposed method, the NN-determined boundaries are compared with those traced by two highly trained surgeons. The author's preliminary results show that the proposed method has potential utility in...

Descriptors: computerised tomography ; ...

... image segmentation...

...medical image processing

...Identifiers: abdominal CT images ; ...

...3-layered neural network ; ...

...medical diagnostic imaging ; ...

... image preprocessing ;

1994

20/3,K/23 (Item 7 from file: 8)  
DIALOG(R) File 8: Ei Compendex(R)  
(c) 2005 Elsevier Eng. Info. Inc. All rts. reserv.

04365106 E.I. No: EIP96033110480

**Title: Determining and classifying the region of interest in ultrasonic images of the breast using neural networks**

Author: Buller, Danuta; Buller, Andrzej; Innocent, Peter R.; Pawlak, Waldemar

Corporate Source: City Hospital, Wejherowo, Pol

Source: Artificial Intelligence in Medicine v 8 n 1 Feb 1996. p 53-66

Publication Year: 1996

CODEN: AIMEEW

Language: English

**Title: Determining and classifying the region of interest in ultrasonic images of the breast using neural networks**

Abstract: This paper describes how **ultrasonic images** of the female breast have been processed and neural nets used to aid the identification of malignant and benign areas in them. The **images** are windowed, filtered and **pre - processed** into suitable patterns for processing by a neural net. Two networks are **trained** and used: one for malignant cases and the other for benign cases. These are used to make predictions of regions of interest which are presented as circles overlaid on the **image**. The system has been prototyped and tested and experts agreed well with the classification and localization. The system is usually weak when the evidence on the **image** is considered weak by the expert. It is concluded that the system is promising and should be developed further by providing more **training** to the network. (Author abstract) 24 Refs.

Descriptors: \*Compute r.aided diagnosis; **Neural networks** ; **Ultrasonic imaging** ; Medical imaging ; Image analysis; Pattern recognition

20/3,K/25 (Item 9 from file: 8)  
DIALOG(R)File 8: Ei Compendex(R)  
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04055613 E.I. No: EIP95012534210

**Title:** Fourier-transformed preprocessing used in a noniteratively-trained perceptron pattern recognizer

**Author:** Hu, Chia-Lun J.

**Corporate Source:** Southern Illinois Univ at Carbondale, Carbondale, IL, USA

**Conference Title:** Proceedings of the 1994 IEEE International Conference on Neural Networks. Part 5 (of 7)

**Conference Location:** Orlando, FL, USA **Conference Date:** 19940627-19940629

**E.I. Conference No.:** 42367

**Source:** IEEE International Conference on Neural Networks - Conference Proceedings 5 1994. IEEE, Piscataway, NJ, USA, 94CH3429-8. p 3020-3023

**Publication Year:** 1994

**CODEN:** 001762

**Language:** English

**Title:** Fourier-transformed preprocessing used in a noniteratively-trained perceptron pattern recognizer

**Abstract:** When a digitized image is preprocessed by spatial quantizations in a polar-coordinate, the analog vectors representing the r and the theta quantizations can be treated separately in neural network trainings. If we apply a segmented Fourier transform (similar to FFT) to the theta vector and a segmented Hankel transform to the r vector in a noniterative perceptron training system, then not only the learning of the training patterns is very fast (e.g., 2 seconds for learning 4 training patterns), but also the recognition of an untrained pattern is very robust. Specially the recognition is very robust when the test pattern is rotated even though all the training patterns are not rotated in space. The high robustness of recognition is due to the special preprocessing scheme and the optimum noniterative training scheme we adopted in the design. This paper concentrates at the theoretical origin and the experimental results of the robustness of this novel perceptron learning system. An unedited video movie of the whole training/recognition experiment is recorded in real time for demonstration purpose. (Author abstract) 5 Refs.

**Descriptors:** \*Neural networks ; Pattern recognition; Image processing; Vectors; Fast Fourier transforms; Learning systems; Real time systems; Optimal systems; Pattern recognition systems; Robustness (control systems)

**Identifiers:** Fourier transformed preprocessing ; Noniteratively trained perceptron pattern recognizer; Spatial quantizations; Non conventional training ; Unsupervised learning

20/3,K/28 (Item 12 from file: 8)  
DIALOG(R)File 8:Ei Compendex(R)  
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03678877 E.I. No: EIP93081044164

**Title: Recognizing cancer cells from images of stomach smears**  
Author: Hong, Qin; He, Zhenya; Wu, Chengwu; Wang, Taijun  
Corporate Source: Southeast Univ, Nanjing, China  
Source: Zhongguo Shengwu Yixue Gongcheng Xuebao/Chinese Journal of Biomedical Engineering v 12 n 1 Mar 1993. p 56-60, 34  
Publication Year: 1993  
CODEN: ZSYXEI ISSN: 0258-8021  
Language: Chinese

**Title: Recognizing cancer cells from images of stomach smears**  
Abstract: This paper discussed the application of **digital image** processing and pattern recognition to the diagnosis of stomach smears. Under the supervision of pathologists, cell **images** are collected and divided into three classes: normal cells, cells between the normal and cancer, and cancer cells. At first, the cell **images** are **preprocessed**. The **images** are enhanced by histogram equalization and median filtering. Then by computing the threshold using the...

...the nucleus of a cell can be segmented. Six features were extracted from the cell **images**. A **neural network** approach for the classification was described. The utilized network is a multilayer perceptrons (MLP). The backpropagation **learning** is used for its **training**: The performance of the MLP was compared to traditional linear classifiers. It is shown that...

Descriptors: \*Biomedical engineering; Gastroenterology; Oncology; Cytology; **Image** analysis; **Image** processing  
Identifiers: Stomach cancer cell; Cancer cell **image** recognizing

20/3,K/31 (Item 15 from file: 8)  
DIALOG(R)File 8: Ei Compendex(R)  
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03531561 E.I. Monthly No: EIM9212-064694

**Title:** Neural network diagnosis of avascular necrosis from magnetic resonance images .

**Author:** Manduca, A.; Christy, P.; Ehman, R.

**Conference Title:** Proceedings of the 13th Annual International Conference of the IEEE Engineering in Medicine and Biology Society

**Conference Location:** Orlando, FL, USA **Conference Date:** 19911031

**E.I. Conference No.:** 17015

**Source:** Proceedings of the Annual Conference on Engineering in Medicine and Biology v 13 pt 3. Publ by IEEE, IEEE Service Center, Piscataway, NJ, USA (IEEE cat n 91CH3068-4). p 1429-1431

**Publication Year:** 1991

**CODEN:** CEMBAD **ISSN:** 0589-1019 **ISBN:** 0-7803-0216-8

**Language:** English

**Title:** Neural network diagnosis of avascular necrosis from magnetic resonance images .

**Abstract:** Artificial neural networks has been used to diagnose avascular necrosis (AVN) of the femoral head from magnetic resonance images . Multilayer perceptron networks, trained with conjugate gradient optimization, which diagnose AVN from single sagittal images of the femoral head with 100% accuracy on the training data and 97% accuracy on test data has been developed. These networks use only the raw image as input (with minimal preprocessing to average the images down to 32 multiplied by 32 size and to scale the input data values) and learn to extract their own features for the diagnosis decision. Various experiments with these networks, whose results are considered to be very encouraging for the use of neural networks in diagnostic radiology, are described.  
9 Refs.

...Descriptors: Computer Aided Diagnosis; NEURAL NETWORKS ;  
MAGNETIC RESONANCE IMAGING ; IMAGE PROCESSING...

... Image Analysis; RADIOGRAPHY

Identifiers: AVASCULAR NECROSIS DIAGNOSIS; NEURAL NETWORK DIAGNOSIS;  
MULTILAYER PERCEPTRON NETWORK; CONJUGATE GRADIENT OPTIMIZATION; DIAGNOSTIC RADIOLOGY

20/3,K/49 (Item 16 from file: 34)  
DIALOG(R)File 34:SciSearch(R) Cited Ref Sci  
(c) 2005 Inst for Sci Info. All rts. reserv.

02334321 Genuine Article#: KV204 No. References: 53  
**Title: ADVANCED MACHINE LEARNING TECHNIQUES FOR COMPUTER VISION**  
Author(s): MOSCATELLI S; KODRATOFF Y  
Corporate Source: CNRS,BAT 490/F-91405 ORSAY//FRANCE/; UNIV PARIS  
11,LRI/F-91405 ORSAY//FRANCE/  
Journal: LECTURE NOTES IN ARTIFICIAL INTELLIGENCE, 1992 , V617, P161-197  
ISSN: \*\*\*\*\*  
Language: ENGLISH Document Type: ARTICLE (Abstract Available)

**Title: ADVANCED MACHINE LEARNING TECHNIQUES FOR COMPUTER VISION**  
**, 1992**

**Abstract: Learning** is a critical research field for autonomous **computer** vision systems. It can bring solutions to the knowledge acquisition bottleneck of **image** understanding systems. Recent developments of **machine learning** for **computer** vision are reported in this paper. We describe several different approaches for **learning** at different levels of the **image** understanding process, including **learning** 2-D shape models, **learning** strategic knowledge for optimizing model matching, **learning** for adaptative target recognition systems, knowledge acquisition of constraint rules for labelling and automatic parameter...

...Research Fronts: FOR CMOS HIGH-PERFORMANCE CIRCUITS)

91-4728 002 (KNOWLEDGE ACQUISITION; DISCOVERY OF PROBLEM-SOLVING STRATEGIES; **LEARNING** PLAN SCHEMATA)

91-1259 001 ( **HOUGH TRANSFORM** ; OBJECT RECOGNITION; **COMPUTER** VISION; RANGE **IMAGES** ; CURVE DETECTION)

20/3,K/55 (Item 2 from file: 35)  
DIALOG(R)File 35:Dissertation Abs Online  
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01539663 ORDER NO: AAD97-11033

**AN AUTOMATED SYSTEM FOR THE CLASSIFICATION OF MAMMOGRAMS ( COMPUTER  
AIDED DIAGNOSIS)**

Author: COOLEY, TIMOTHY RICHARD

Degree: PH.D.

Year: 1996

Corporate Source/Institution: RUTGERS THE STATE UNIVERSITY OF NEW JERSEY  
- NEW BRUNSWICK (0190)

Source: VOLUME 57/11-B OF DISSERTATION ABSTRACTS INTERNATIONAL.  
PAGE 7073. 191 PAGES

**AN AUTOMATED SYSTEM FOR THE CLASSIFICATION OF MAMMOGRAMS ( COMPUTER  
AIDED DIAGNOSIS)**

Year: 1996

This dissertation describes a new approach to the automated processing of **mammograms**. Previous research centered on **Computer Aided Diagnosis** (CAD) which assists a radiologist in their interpretation of the **image**. Oftentimes these systems would only process manually specified regions of the **mammogram**. This system takes a **mammogram** as a whole and classifies it as normal (Category I) or abnormal (Categories II, III...

...of system could be used as a first screening tool for locations that have no **trained** radiologist. One such location is the mobile **mammography** vans which perform screening **mammography** at various places. It could also be of use in a "second opinion" role providing additional information to a **trained** radiologist.

The system is composed of three distinct modules: **Image** acquisition, **Image** pre-processing, and **Image** classification. To acquire the **digitized image** the **mammogram** is scanned with a flat-bed transparency scanner at a resolution of less than 65  $\mu\text{m}$ . The **digitized mammogram** is then **pre - processed** by a five octave, multi-resolution wavelet transform. Features are extracted by the novel technique...

...Additional features are obtained by computing the invariant moments and the entropy of the original **image**. These features are then used to classify the **mammogram** by a modular feed-forward **neural network** which is **trained** using the ALOPEX optimization algorithm.

The system was **trained** on 49 **mammograms**, 28 normals and 21 abnormals, and tested on 10 **mammograms**, 6 normals and 4 abnormals. **Training** performance of greater than 93 percent was consistently achieved. By curtailing the **training** prior to the network becoming overtrained, validation performance of 100 percent was reached. Since **mammograms** are viewed as one of the most difficult **images** to process, these methods should also perform well with other **image** types.



20/3,K/70 (Item 8 from file: 144)  
DIALOG(R)File 144:Pascal  
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12802423 PASCAL No.: 97-0015512

**Application of neural network -based multi-stage system for detection of microcalcification clusters in mammogram images : Computer -aided diagnosis I**

Image processing : Newport Beach CA, 12-15 February 1996

LURE F Y M; GABORSKI R S; PAWLICKI T F

LOEW Murray H, ed; HANSON Kenneth M, ed

Eastman Kodak Company, Rochester, NY 14650-2123, United States

International Society for Optical Engineering, Bellingham WA, United States.

Image processing. Conference (Newport Beach CA USA) 1996-02-12

Journal: SPIE proceedings series, 1996 , 2710 16-23

Language: English

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**Application of neural network -based multi-stage system for detection of microcalcification clusters in mammogram images : Computer -aided diagnosis I**

Image processing : Newport Beach CA, 12-15 February 1996

1996

A multi-stage system with image processing and artificial neural techniques is developed for detection of microcalcification in digital mammogram images . The system consists of (1) preprocessing stage employing box-rim filtering and global thresholding to enhance object-to-background contrast ; (2...

... erosion, connected component analysis, and suspect region segmentation to select potential microcalcification candidates ; and (3) neural network -based pattern classification stage including feature map extraction, pattern recognition neural network processing, and decision-making neural network architecture for accurate determination of true and false positive microcalcification clusters. Microcalcification suspects are captured and stored in 32 x 32 image blocks, after the first two processing stages. A set of radially sampled pixel values is utilized as the feature map to train the neural nets in order to avoid lengthy training time as well as insufficient representation. The first pattern recognition network is trained to recognize true microcalcification and four categories of false positive regions whereas the second decision...

... identify true cluster at an accuracy of 93% with 2.9 false positive microcalcifications per image .

English Descriptors: Malignant tumor; Mammary gland; Woman; Mammography ; Computer aid ; Diagnostic aid; Digital image ; Microcalcification; Diagnosis; Neural network ; Multistage process; Image processing; Image analysis

French Descriptors: Tumeur maligne; Glande mammaire; Femme; Mammographie ; Assistance ordinateur; Aide diagnostic; Image numerique; Microcalcification; Diagnostic; Réseau neuronal; Procédé étage; Traitement image ; Analyse image

Spanish Descriptors: Tumor maligno; Glandula mamaria; Mujer; Mastografía; Asistencia ordenador; Ayuda diagnóstica; Imagen numerica; Microcalcificación; Diagnóstico; Red neuronal; Procedimiento

poliescalonado; Procesamiento **imagen** ; Analisis **imagen**  
Broad Descriptors: Human; Mammary gland diseases; Biomedical engineering;  
Biomedical **data processing** ; Radiodiagnosis; Homme; Glande mammaire  
pathologie; Genie biomedical; Informatique biomédicale; Radiodiagnostic;  
Homme; Glandula mamaria patologia; Ingenieria...

20/3,K/75 (Item 4 from file: 155)  
DIALOG(R) File 155:MEDLINE(R)  
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10997191 PMID: 7777543

Neural - network -based classification of cognitively normal, demented, Alzheimer disease and vascular dementia from single photon emission with computed tomography image data from brain.

deFigueiredo R J; Shankle W R; Maccato A; Dick M B; Mundkur P; Mena I; Cotman C W

Department of Electrical and Computer Engineering, University of California, Irvine 92717, USA.

Proceedings of the National Academy of Sciences of the United States of America (UNITED STATES) Jun 6 1995 , 92 (12) p5530-4, ISSN 0027-8424  
Journal Code: 7505876

Contract/Grant No.: AG05142; AG; NIA

Publishing Model Print

Document type: Journal Article

Languages: ENGLISH

Main Citation Owner: NLM

Record type: MEDLINE; Completed

Neural - network -based classification of cognitively normal, demented, Alzheimer disease and vascular dementia from single photon emission with computed tomography image data from brain.

Jun 6 1995 ,

Single photon emission with computed tomography (SPECT) hexamethylphenylethyleneamineoxime technetium-99 images were analyzed by an optimal interpolative neural network (OINN) algorithm to determine whether the network could discriminate among clinically diagnosed groups of elderly normal, Alzheimer disease (AD), and vascular dementia (VD) subjects. After initial image preprocessing and registration, image features were obtained that were representative of the mean regional tissue uptake. These features were extracted from a given image by averaging the intensities over various regions defined by suitable masks. After training , the network classified independent trials of patients whose clinical diagnoses conformed to published criteria for...

...80 and 86% for probable AD and probable/possible VD, respectively. These results suggest that artificial neural network methods offer potential in diagnoses from brain images and possibly in other areas of scientific research where complex patterns of data may have...

Descriptors: \*Alzheimer Disease--radionuclide imaging --RI; \*Brain --radionuclide imaging --RI; \*Dementia, Vascular--radionuclide imaging --RI; \* Neural Networks ( Computer ) ...; Middle Aged; Organotechnetium Compounds--diagnostic use--DU; Oximes--diagnostic use--DU; Technetium Tc 99m Exametazime; Tomography , Emission-Computed, Single-Photon

Set	Items	Description
S1	449547	IMAGE? OR IMAGING? OR GRAPHIC? OR VIDEO? OR BITMAP? OR BIT- ( ) (MAP OR MAPS OR MAPPED OR MAPPING)
S2	74183	SONOGRA? OR VISUAL? OR ULTRASOUND? OR ULTRASONIC? OR PICTO- RIAL? OR XRAY? OR X( ) (RAY OR RAYS OR RAYED OR RAYING) OR RADI- OGRA?
S3	34955	PHOTOGRAPH? OR PET(2N)SCAN? OR PETSCAN? OR POSITRON( )EMISS- ION? OR MAGNETIC? ( ) RESONANC? OR MRI
S4	1290	TOMOGRAPH? OR MAMMOGRA? OR CATSCAN? OR (CAT OR CT) ( ) SCAN? - OR CTSCAN?
S5	1006260	COMPUTER? OR DIGITAL? OR DIGITIZ? OR DIGITIS? OR BINARY?
S6	118467	DATAPROCESS? OR MICROPROCESS? OR CENTRALPROCESS? OR (MICRO OR DATA OR CENTRAL) ( ) PROCESS?
S7	11818	PROCESS?(2N) (MODULE? OR UNIT?)
S8	252	SVM OR SUPPORT( ) VECTOR? OR VECTOR( ) MACHINE?
S9	17238	MACHINE?(2N) LEARN? OR MACHINE( ) VECTOR? OR NEURAL( ) NETWORK? OR ARTIFICIAL( ) (NEURAL? OR INTELLIGEN?) OR BACK( ) PROPAGAT? OR OPTIM?( ) (HYPERPLAN? OR HYPER( ) PLAN?) OR CYBERNET?
S10	4290	PREPROCESS? OR PREANALY? OR PREEXAMIN? OR PREPARS? OR (BEF- ORE? OR PRIOR? OR PRELIMIN? OR PREPARAT?) (2W) PROCESS?
S11	26089	IDENTIF?(3N) (MISSING? OR ERROR? OR ERRONEOUS? OR FLAW?) OR TRANSCOD? OR DATA(3N) (MODIF? OR CONVERT? OR CONVERSION? OR AL- TER? OR CHANGE? OR CHANGING)
S12	581	TRANSFORM? ?(3N) (RADON OR HOUGH) OR PRECLASSIF? OR PRE( ) (P- ROCESS? OR ANALY? OR EXAMIN? OR PARS? OR CLASSIF?)
S13	343198	TRAIN? OR LEARN? OR EDUCAT? OR INSTRUCT? OR TEACH? OR TAUG- HT? OR DIDACT? OR SELFTEACH? OR AUTODIDACT?
S14	448	S1:S4 AND S5:S7 AND S8:S9 AND S10:S12 AND S13
S15	394	S14 AND PY<2000
S16	364	RD (unique items)
S17	147	S16 AND S1:S4(5N)S5:S7
S18	32	S17 AND (PREPROCESS? OR PRE( ) PROCESS?)

? show files

File 275:Gale Group Computer DB(TM) 1983-2005/Jun 01

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File 647:CMP Computer Fulltext 1988-2005/May W3

(c) 2005 CMP Media, LLC

File 674:Computer News Fulltext 1989-2005/May W4

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?

18/3,K/14 (Item 14 from file: 275)  
DIALOG(R) File 275:Gale Group Computer DB(TM)  
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01553332 SUPPLIER NUMBER: 13377714 (USE FORMAT 7 OR 9 FOR FULL TEXT)  
Is neural computing the key to artificial intelligence ? (includes  
related articles on an explanation of neural computing, neural net chip  
speeds, neural computing challenging the status quo, digital signal  
processing and neural nets in medical research, and using neural nets in  
manufacturing loud speakers)  
Donlin, Mike; Child, Jeffrey  
Computer Design, v31, n10, p87(14)  
Oct, 1992  
ISSN: 0010-4566 LANGUAGE: ENGLISH RECORD TYPE: FULLTEXT; ABSTRACT  
WORD COUNT: 8391 LINE COUNT: 00699

Is neural computing the key to artificial intelligence ? (includes  
related articles on an explanation of neural computing, neural net chip  
speeds, neural computing challenging the status quo, digital signal  
processing and neural nets in medical research, and using neural nets in  
manufacturing loud...

ABSTRACT: Advances in **neural network** technology has created increased  
interest in the thinking power of **computers** . In particular, there has  
been a renewed interest in neural computing in connection with **digital**  
signal processing, pattern recognition and forecasting. Certain common  
characteristics are shared by all **neural networks** . In the first place,  
they use some form of **learning** model to create their own representation  
of reality. Secondly, they use artificial neurons that are connected to at  
least one other neuron. Detailed is a history and explanation of **neural**  
**networking** . Areas discussed include **learning** by example, fuzzy logic,  
fast- **learning** chips, software-only **neural network** -specific products,  
the financial uses of neural computing and the impact of **neural networks**  
.

TEXT:

When people speculate about whether **computers** can **learn** to think,  
evil robots, such as Nomad running amok on the Starship Enterprise, often  
enter...

...Captain Kirk talks the sinister Nomad into blowing itself up, but the  
notion of a **computer** that can control human destiny makes many folks  
nervous. **Computer** professionals scoff at such silliness, even while  
acknowledging that advances in hardware and software have given **computers**  
the ability to emulate some human traits.

... room and could rip through mathematical calculations at a  
blistering 13 operations a second.

Presently, **computer** technology resides somewhere between ENIAC and  
Nomad, but advances in **artificial intelligence** , and particularly in  
**neural networks** , have caused a surge of interest in the thinking power  
of **computers** .

Nothing new about **neural networks**

The concept of **neural networks** has been around in some form since  
World War II, but it's only in the last six or seven years that working  
products have been developed that attempt to " **learn** " about and predict  
reality. In their infancy, **neural networks** and neural computing were  
the work of theorists who observed similarities in the way that **computers**  
and humans think. In both cases, a large amount of information is  
manipulated by breaking it into small particles--using gates in **computers**

and neurons in humans. Gates handle data by fluctuating between an "on" and "off" state...

...if the neurons were connected but not firing. Because of these similarities between human and **computer** thought, researchers have begun to explore ways to embody the structures of human intelligence in...  
...100 billion neurons, each connected to 10,000 others by synapses. Building such a complex **computer** is a ridiculous idea, even with the staggering advances made in **computer** technology in the last twenty years.

Also, **neural networks** were dealt a blow in 1969 when Marvin Minski and Seymour Pappert wrote a book called Perceptrons, which postulated that **neural network** research was a waste of time. Minski, one of the founding fathers of the **artificial intelligence** movement, refused to believe that software could simulate the behavior of human neurons. Minski's vision of **artificial intelligence** (M) was far more comprehensive than just **neural network** technology, and he scoffed at those who wanted to reduce his broad theories to a...

...of equations that could solve only simple problems. Many experts blame this book for derailing **neural network** research and encouraging the expert-system theories favored by the authors.

Expert systems, in turn...

...Although there are some areas where encoding the skills of an expert and programming a **computer** to carry them out seem feasible, for most complex tasks the intuition of an expert...

...expert makes decisions," says Steve Bissett, senior vice-president at Synaptics (San Jose, CA), a **neural network** IC firm. "The problem is that most experts can't tell you all the rules..."

...difficult to codify. Even if you could write out enough knowledge to program into a **computer**, the amount of data would be so large that it would be prohibitively expensive to...

...emulate the neural connection model of the brain, both in hardware and in software, all **neural networks** share certain common characteristics: they use artificial neurons that are connected to at least one other neuron, and they create their own representations of reality based on some form of **learning** model.

I **Learning** by example

Fundamentally, all **neural networks** **learn** by association. For example, a **neural network** can **learn** to identify an apple by associating the inputs "round," "red" and "fruit" with the output "apple." The neurons in a **neural network** are usually organized in three layers: input, hidden and output. Sometimes more than one hidden layer is used for complex analysis.

There are many ways that **neural networks** can **learn**, but the most common way is through example and repetition, also called **back-propagation**. Each time an input is given to the network ("round," "red" or "fruit" from our...

...data, it will begin to zero in on the right answer. When it's fully **trained**, it can deliver an answer that's more or less accurate, depending on the complexity...

...this ability to gauge the importance of data that separates neural computing from a purely **digital** computational process. Although the synapses and weights can be made up of analog circuitry, **digital** components or software, the weighting procedure makes neural computing

appear to have an analog nature...

...as pattern recognition or financial forecasting.

"There's a key difference between neural computing and **digital** computing," Synaptics' Bissett points out. "Traditional **digital** computing is like the left-brain or logical thinking that we do. The **computer** receives a set of rules or programs, then takes input and produces output based on...Neural computing is more like right-brain thinking, which is intuitive. If you wanted a **computer** to read handwriting, you could try to write rules that would make it recognize an...

...previous knowledge to try and categorize it. An important distinction, then, is to try and **teach** by example rather than programming by rules."

The correlation of **neural networks** to the way our brains work is what makes them suited to applications that need experiential **learning**, but is neural computing really thinking? In a word, no. **Neural networks** are patterned after the architecture of the brain, but in reality their ability to think...

...a common housefly. As a matter of fact, some experts scoff at the notion that **neural networks** are related to human thought at all, other than in a purely analogous way.

"It...

...has nothing to do with building brains," says Casimir Klimasauskas, president of NeuralWare (Pittsburgh, PA). "**Neural networks** are a collection of mathematical techniques that let you fit formulas to data, curves to data, and group types of data together. **Neural networks** could have been invented by statisticians, physicists or mathematicians, but the people who invented them were cognitive psychologists and neurobiologists, and so we ended up with the term **neural networks**. They have nothing to do with brains. I've found that if you try to explain **neural networks** from a human-thought perspective, people keep trying to fit them into a brain model..."

...Enter fuzzy logic

In spite of such caveats, most people will probably continue to associate **neural networks** with human thought, particularly because much of the **learning** process in a **neural network** takes place in hidden layers or neurons, a processing paradigm similar to human thought. Some...

...functions by using fuzzy logic techniques to better understand, or even work in conjunction with, **neural networks**. Fujitsu (Kawasaki, Japan) is working on a system, for example, that creates a fuzzy rule...

...questionnaires that have been filled out by experts. These fuzzy systems are converted into a **neural network**, which **learns** about the task and refines its knowledge. Once the **neural network** has achieved an acceptable degree of accuracy, it's translated back into a fuzzy system...

...analyzed. According to Fujitsu researchers, this model reveals the hidden variables that develop in a **neural network**. By keeping the fuzzy rule sets and the **neural networks** as separate systems, the Fujitsu scientists believe they can **learn** more about how each system works.

But not everyone involved in combined fuzzy/neural computing...

...the disciplines separate. There's considerable activity in the AI community aimed at combining the **neural network**'s ability to create relationships with fuzzy logic's capability to produce input and output information that spans a range of behavior. One such approach builds fuzzy operations into the **learning** techniques used by a fuzzy/neural.

controller. The resulting **neural network** **learns** to emulate a fuzzy controller, but with rules that can be altered by **neural learning** techniques.

In spite of the promise that the combination of fuzzy logic and **neural networks** holds, most of the work in this area is at the theoretical stage, although some practical applications have been demonstrated in medical **imaging** and flight simulation. To many theorists, however, the marriage of these two "smart" technologies seems inevitable.

Theories aside, most of the tangible products using either fuzzy logic or **neural networks** have come from research that treats each of these disciplines as separate entities. In the field of **neural networks**, this means three categories of products: **neural network** ICs, whose architectures are specifically designed for neural computing; **neural network** software, which uses standard **microprocessors** and **digital** signal processors to emulate **neural network** behavior; and **neural network** systems, which are turnkey **neural network** computers.

The first commercially available **neural network** specific chip was the 80170NX electrically **trainable** analog **neural network** (ETANN) device from Intel (Santa Clara, CA). Introduced in 1989, the chip is a 64 ...

...64 synapse arrays.

Intel has also released a development system so that you can simulate, **train** and operate a high-speed **neural network**. Dubbed the Intel **Neural Network Training System** (iNNTS), the package provides two 80170NX devices, two **learning** simulation software programs, diagnostic software, a programmer interface, an adapter that can run on PC/AT-compatible **computers**, programming specifications, and full documentation. The iNNTS contains two **learning** simulation software programs, iBrainmaker and DynaMind. The iBrainmaker program, developed by California Scientific Software (Grass Valley, CA), lets you simulate the **network learning** process through **back - propagation** techniques. In **back propagation**, you present the network model with a data set representing the application problem. Through simulation, iBrainmaker then **trains** the network to produce a desired response to specific inputs by assigning weights to each of the chip's analog storage elements. Once the network has been **trained** to solve the application problem, the weights are downloaded or programmed into the ETANN device.

The DynaMind simulation software, developed by NeuroDynamX (South Pasadena, CA), lets you simulate **back - propagation learning**, but also performs chip-in-loop **learning**. This technique optimizes the performance of the network by replacing the software simulation of the chip's performance characteristics and specifications with an actual device. The **neural network** can then "**learn** around" any minor processing variations occurring in individual ETANN chips.

Both iBrainmaker and DynaMind can also be used independently of the Intel development system to create **neural network** applications.

I Fastest- **learning** chip

A more recent **neural network** IC is the RN-200, a 256-synapse (16 synapses x 16 neurons) device that Ricoh (Tokyo, Japan) claims is the world's fastest- **learning** chip of its kind. The device boasts a front-end process of three billion connections per second and a **learning** speed of 1.5 billion connection updates per second (CUPs) when running at 12 MHz. In Tokyo, Ricoh demonstrated a desktop **neural computer** system that requires no software. Based on the first-generation RN-100 chip (a one...

...says will increase when the system incorporates the new RN-200.

One of the first **neural network** ASICs comes from Neural Semiconductor (Carlsbad, CA). Its CNU3232 has 32 inputs, 1,024 synaptic



weights and 32 nodes supporting its activation functions. The one-byte **digital** inputs and outputs and the weight-storage SRAM are all accessed through an 8-bit...

...0 bus. Unlike the Intel chip, which uses analog elements, the CNU3232 is a purely **digital** device that's targeted at embedded system applications.

"We refer to ourselves as a neural...

...company," says Robert Bagby, president of Neural Semiconductor, "because we expect our customers to build **neural network** ICs of various sizes, topologies, precisions, and activation functions using our basic architecture. **Neural networks** are really multiple layers of nonlinear matrix multipliers. We build discrete circuitry for each and...

...have fully parallel neurons and fully parallel synapses or weights. Because our architecture is purely **digital**, designs based on it can be manufactured with standard processes for low-cost, high-volume "implementations."

The first **neural network** IC to find its way into a commercially available product comes from Synaptics. The chip, designed for optical character recognition (OCR), hosts an analog sensing array, two **neural networks** and a **digital** controller on a single device. The chip is at the heart of a check reader...

...says Synaptics' Bisset. "For most applications using a TV camera, that rate was just 30 **images** per second. By putting the sensor on the same chip with the classification circuitry, we...

...the same task thousands of times per second."

Other solutions

Not all hardware solutions for **neural network** applications are based on neural-specific silicon. There are systems that use standard **digital** components for neural computing, as well as for non-neural applications such as Fourier or...

...each with its own 4 kbytes of on-chip SRAM. A PN resembles a simple **digital** signal processor (DSP), and can be programmed for a variety of applications. At 25 MHz...

...billion multiply-adds per second. The chip falls somewhere between PC-based software solutions for **neural network** applications and silicon that's targeted at those applications.

"Given the performance of today's PCs and workstations, you can emulate a lot of **neural network** applications in software alone," says Dan Hammerstrom, founder and chief technical officer at Adaptive Solutions ...

...chip. That's where flexibility pays off." I Software-only solutions The remaining category of **neural network**-specific products is software-only solutions, which emulate **neural networks** on workstations, PCs and mainframes. These programs use either standard **microprocessors** or DSP chips to perform **neural networking** tasks, and are available from dozens of companies. The applications are as diverse as the...

...are being used for pattern recognition, financial analysis and defense-related projects.

In essence, most **neural network** tasks are based on some form of pattern recognition. Sometimes the sought-after pattern is a **visual** one--for example, a system that sorts good fruit from bad on a conveyor belt. In this application, the network must be **trained** to look for a vague trait such as "quality." "The customer who wanted to grade fruit had

to **train** the network to recognize color patterns that distinguished good apples from bad," says Ted Crooks, director of customer services at HNC (San Diego, CA), a **neural network** software vendor. "By repeatedly presenting data to the network, he **trained** it to discern the important relationships that define good quality--for example, 'this is premium...

...just gave examples of what characteristics are needed to place a piece of fruit there."

**Visual** pattern recognition is also being applied to medical research. Some hospitals are using a **neural network** to sift through hundreds of slides to detect anomalies in blood cells or tissue samples. Early results from these applications show that **neural networks** achieve a surprising level of accuracy when they're compared to a human performing the same task. As with most applications where a **computer** equals or bests a human being at a task, fatigue is the deciding factor. Although...human fatigue can cancel out some of that expertise, and the capabilities of human versus **neural network** begin to equalize.

In addition to recognizing flaws in cell structure, some physicians are using **neural networks** to help them with diagnosis and prognosis. "One of our customers is a neurosurgeon who's using **neural networks** to predict potential IQ loss after brain surgery," says Jim Blodgett, director of marketing for...

...statistics are fine. But in the middle of the curve there can be large variations. **Neural networks** can use factors such as the severity of an injury or a patient's medical history to make predictions of an operation's outcome ." I Financial uses While **neural network** research in medicine makes for dramatic reading, there are other applications, particularly in the realm of finance, that might have even greater ramifications. Banks are relying on **neural networks** to do everything from predicting loan eligibility to spotting credit-card fraud. In the case of loan eligibility, the network is **taught** to examine the factors that would make a good loan applicant, based on profiles of...

...the data, such as income, time on the job, credit history, and so on, but **neural networks** look for unusual patterns or relationships which might escape a human, particularly a human who...

...a gourmet meal in a 24-hour period.

The common denominator in these applications is **training** the network to look for subtle shifts in paterus which are crucial to making a ...

...which stocks produce returns better or worse than expected."

The lure of networks

Obviously, developing **neural networks** that can accurately predict what was once thought to be unpredictable is a tantalizing prospect...

...of these stories sound like hype, especially when they're playing to an audience of **computer** professionals who've seen their share of flash-in-the-pan technologies over the years. Still, there is an element of mystery to many **neural network** applications.

"We think there's a lot more going on, particularly in financial circles, than...

...the only area where more mystery prevails than on Wall Street is in defense-related **neural network** applications. Most of the people involved in such projects are understandably reluctant to discuss the details of their activities, but it's clear that **neural networks** are being used for such things as missile guidance systems.

"We became interested in **neural networks** about six or seven years ago, when other **artificial intelligence** solutions proved to be too slow for our applications," says Dr. David Andes, research fellow...

...all, the purpose of the device is to deliver explosives, not electronics. We got into **neural networks** because biological brains do the type of computing that we need, and they do it...

...stem that can hit a target without needing human intervention.

Naturally, for these applications a **neural network** must be **trained** to recognize a target in the confusion of battle, something that heat-seeking devices find problematic. But trying to give a **neural network** enough data to find targets in rapidly changing battle situations is a daunting task.

"**Neural networks** are notorious for picking up on things that you don't want them to," Andes cautions. "We heard about one application where a **neural network** was picking out the enemy from a **visual** field with perfect accuracy. Naturally, everyone got suspicious and investigated more closely. It turned out..."

...no hum, good guy. They took away the hum and the network was lost." I **Neural network**'s impact When the breadth of **neural networking** applications is ...to separate fact from fiction is difficult, particularly when those who are really successful with **neural networks** are reluctant to divulge too many details. And so the questions remain--can you use a **neural network** in your job, and how will **neural networks** ultimately affect your life?

As far as jobs are concerned, **neural networks** are best suited to analytical tasks that prove too complex or firing for humans to perform accurately. And certainly because **neural networks** are based on **computer** technology, they will affect the electronics industry if they're widely embraced.

Technological applications of **neural networks** are, in fact, starting to see the light of day. Last February, for example, Intel announced a breakthrough in **neural networking**, the capability not only to identify patterns but also to read out their locations. The...

...at 6 o'clock--like a pilot reporting an enemy's position in the sky.

**Neural networks** could also conceivably guide placement and routing algorithms for chip and printed circuit board design...

...your spine, you're not alone. Although it's far too soon to predict whether **neural networks** are another headline-grabbing M story or the beginning of a **computer** revolution, one thing is clear. The **photographs** that accompany this article are taken from real applications. Somewhere a **computer** might be grading the apples that you eat. It may be deciding whether to give...

...a job interview. And because most of you reading this article are familiar with what **computers** can and can't do, you're either smiling fight now--or feeling a little queasy.

In these examples of pattern recognition from HNC, the **neural network**'s ability to **learn** by association shows the technology to be promising for everything from fruit grading to target recognition for weapons systems.

The apple grading system captures **images** and feeds them to a **neural network**, which eventually **learns** how to determine which characteristics affect an apple's quality. Once the network is **trained**, the system can classify an apple by comparing its traits to the network's **learned** base.

"The tank recognition system," says Ted Crooks, director of customer

services at HNC, "was actually an experiment to prove that **neural networks** could be used in defense systems. Critics of **neural networks** cited an application where a **trained** neural system picked out tanks flawlessly until it was discovered that all pictures of tanks...

...As soon as those clues were taken away, the network failed. We proved that a **neural network** could indeed be **trained** to differentiate a tank's shape from other objects, and that experiment led to a real application,"

In this picture, a filtered **image** of two tanks is outlined so that the network can **learn** to differentiate them from other objects.

For this Special Report on Future Computing, **Computer Design** interviewed Carver Mead, an expert on the subject of neural computing. Professor Mead is the Gordon and Betty Moore Professor of **Computer Science** at the California Institute of Technology, where he has **taught** for 20 years. He's also a co-founder and chairman of Synaptics, a company that develops **neural network** technology Mead has pioneered in many areas of electronics, from the invention of the MESFET to silicon compilers and, recently, VLSI analog neural systems.

**Computer Design**: After many years of use in academic circles, neural computing now appears poised to...

...Mead: Your question reminds me of how people used to talk about parallel architectures in **computers** years ago. People said: "We do things in a topdown way." And I'd ask...

...the beginning, so you have to evolve your understanding along with the application.

In the **neural network** business that top-down approach has translated into some rather abortive attempts to make general-purpose **neural network** chips. Those chips haven't worked well because no one knows what architecture is right...generalize from.

CD: How will future advances in VLSI process technology influence the capabilities of **neural network** chips? Do you see any potential roadblocks? Mead: Silicon process technology is very relevant to neural computing. A lot of people have tried to invent brand-new technologies to do **neural networks**. But it's important to remember that we are riding on the coattails of a...

...immediately applicable to this adaptive analog approach. That's not true of other approaches to **neural networks**.

Transistors as analog devices

CD: As I understand it, your neural net chip uses the transistors in **digital** semiconductors in an analog way.

Mead: Yes. Transistors are analog devices. Let them be what they are. **Digital** IC designers have had to work so hard to turn them into 1s and 0s ...

...The inputs and the intermediate signals are inherently analog signalsthey're typically faked out by **binary** numbers right now in a **computer** simulation, but that's not the effective way to use them. The effective way is for them to evolve in real time as analog signals. **Digital computers** not only turn signals into **digital** values, but they also use discrete time. Those discrete time stamps actually destroy information by aliasing. And because a **neural network** is nonlinear, there's no theory that tells you how much information you've lost...

...way.

Fortunately, the transistors in semiconductors never did know that they were supposed to be **digital**. They're inherently analog by nature.

That means you can use them that way, and...

...s why the adaptive part is so important. Because, not only do you let the **neural networks** learn from their environment, but they also adapt to changes in the environment. And one of...

...in this path. In fact, we're seeing that as the technologies are evolving for **digital** use, they're actually evolving capabilities that we use in an analog way to make them even more effective.

The analog-**digital** continuum CD: It seems clear that neural computing is not destined to replace traditional logical...

...of a pixel or the value of a waveform, to take two examples. And the **digital** world deals with discrete symbols: the letters of the alphabet, for example. At some point...

...the classifier was a relay. Then you had a contact closure and that was your **digital** output. It turned on a light or a heater element in a furnace or something...

...antialias filtering and a multiplexer on the analog side. Then there's an analog-to-**digital** converter, which you could think of as the most brain-dead classifier you can imagine. Because all it does is take analog values and convert them into **binary** numbers which represent voltage changes. The **computer** is expected to manipulate these values as if they were numbers and eventually simulate a...

...example, you'd want to classify the data into phonemes. Our 1-1000 chip classifies **images** directly into character codes. A character code is a lot more meaningful to the **computer** than the analog values of the pixels.

**Computers** are the way to handle discrete symbols, but they ought to be appropriate discrete symbols...

...You use an analog classifier to decide what the best classification is. That has a **digital** output which goes into a **digital** system.

Many of the **neural network** chips available today are aimed at that classifier job. But they're leaving out all...

...end of the spectrum is done by adaptive analog technology and the stuff on the **digital** end is done by **digital computers** (as it is today). And the classification in the middle, between the two, is done...

...level. And that's just plain good engineering. So we're not talking about replacing **digital computers**. It's just a matter of recognizing which technology is most natural for each situation.

CD: Today a lot of **neural networks** are simulated in software on large, powerful **computers**.

Mead: Right. It takes too much **digital** computing for the size of the problem. That limits the applications to the very few, where time isn't critical and you've got the processing power of a Cray **computer** around. It's only by getting this balance in the technologies that we're going...

...or 10 years from now?

Mead: If you look at the continuum between analog and **digital**, we've gone all the way from 90 percent of the system being on the analog side to 90 percent on the **digital** side. We're headed back toward a balance of about half and half. Over the...

...in general are headed.

Any biomedical technician can probably do a better job than a **computer** of **visually** identifying reactions in blood cells. But when

researchers at the University of California (Davis, CA...

...day, and do so accurately and consistently, they moved to an automated approach that combines **digital** signal processing (DSP) with a **neural network** simulated in software.

At first glance, the application seemed like a simple **image** classification problem. Bloodcell **images** are captured using a high-resolution CCD (chargecoupled device) camera attached to a microscope. Each **image** is about a millimeter and a half in diameter. That area contains about 100,000...

...may or may not occur. The photos show four degrees of reaction into which the **neural network** classifies **images**.

There's added complexity, however, because no two reactions are exactly the same. The network also has to account for rotated views of the exact same **image**. For example, if a human were looking at the **image** and felt he or she could better identify the reaction from another angle, the **image** could simply be rotated. For the **computer** this would be very complicated. You'd have to show the network how the **image** looked rotated 5 degrees, and that means the network would have to analyze 72 different versions of the same **image**. In **back - propagation** neural nets, the difficulty of **training** increases proportionally to the number of **training** examples raised to the third power.

#### **Preprocessing** needed

"In **neural networks**, the more work you can do before you hand off the project to the neural...

...are," explains Wasyl Malyj, associate development engineer at uc Davis. With this in mind a **preprocessing** step was included to extract from the blood-cell **image** only its most critical data.

To accomplish this, a two-dimensional Fast Fourier Transform (FFT) is performed on the **image**'s pixel **data**, **converting** it into the frequency domain. This produces a compact feature vector. Sampling algorithms are applied to these vectors to extract useful information. The goal of the **preprocessing** is to take a very complex **image** with upwards of 512 x 512 (or over 1/4-million) pixels and extract from that a few hundred bytes of data. "The **preprocessing** reduced the amount of stuff that the neural net didn't need to **learn**, simplifying its structure, its **training**, and making it possible to implement the neural net with today's technology," says Malyj.

After the **image** is compressed into a complex feature vector, the vector is fed into the neural net...

...information through the net lets it adjust its connection strengths, and in this way it "**learns**" to associate particular spectral patterns with particular reactions.

Because of the **preprocessing**, the input stage of the neural net is typically 128 neurons. To implement the network, the uc Davis researchers developed in software a custom-written **back - propagation** simulator capable of building nets with three or four layers. The code was written to run on a 486 working in conjunction with a Motorola 96002 floating-point **digital** signal processor (DSP).

The input layer typically has 128 neurons. The hidden, or middle, layers...

...covering the specimen, lack of blood or reagent in the reaction well, and proper focus.

**Training** the net According to Malyj, it took only about six hours to **train** the neural net. The DSP hardware helped boost its speed. A **training** set of about 800 **images** was shown to the neural net, along with the classification under which each **image** belongs. Once the neural net was **trained**, technicians began to feed it **images** that it had never seen

before for classification.

The network can be adjusted for various...

...as good as a human. But if we tell the net to classify only those **images** about which it's 'confident,' and to flag the others for us to take a look at, then it classifies about 85 percent of the **images** at better than 99 percent accuracy."

Researchers can then take the remaining 15 percent of the **images** and, after they've been scored by a human, use them to retrain the network ...

...applications that are suited for neural computing are tasks at which humans are better. But **computers** have an advantage over humans. They don't get tired or bored--even after several...

...repetitious work. With this in mind, engineers at CTS (Matamoros, Mexico) made use of a **neural network** in their loudspeaker manufacturing process.

At its plant, CTS manufactures several million loudspeakers per year. To ensure the quality of the units, a final inspection was performed by a **trained** operator, skilled at identifying audio defects.

This method had some disadvantages. An operator was required...

...that point that Rick Bono, a design engineer at CTS, decided to try using a **neural network** to classify the results of production testing. A **back - propagation** neural net was established, consisting of 10 input nodes, 18 hiddenlayer nodes and 4 output...

...four possible outputs identify good speakers and three classes of defective units.

To **train** the neural net, CTS ran over 200 units, both good and bad, through the process...

...classifying them into one of the four output classes. This required about 20 minutes of **computer** time on a 25-MHz 486. Once the network was **trained**, Bono integrated it into the test software using the NeuroShell run-time code generator from...

...now considering developing a second-generation system which would incorporate new cases as it works, **train** invisibly and then implement the new network. This would require a hardware-based implementation of **back - propagation**, says Bono.

Other upgrades might include adding more output nodes to the neural net. "We...

...seen different cases pop up--different defect cases that weren't included in the original **training**," says Bono. "They have distinct patterns, and the net can be **trained** to recognize them."

#### DEVELOPMENT TOOL VENDORS

List courtesy of Martin Middlewood and Tom Schwartz.

##### Adaptive Solutions

CNAPS: Development environment includes CNAPS assembler and library of **neural network** algorithms.  
(503) 690-1236

##### AI Ware

N-NET EX: User and program interfaces, functional link net architecture, associative recall. Supervised and unsupervised **learning**.

(216) 421-2380  
AND America  
HNet: Neural-based development system using digital holography...

...Transputer- and Pc/Windows-based versions.  
(416) 569-0897 (Canada)  
Applied Cognetics  
WinBrain: Develops **back propagation** networks. Incorporates multiple transformational models.  
(212) 969-8769  
California Scientific Software  
Brainmaker: Basic...

...neurons, up to six hidden layers. Tutorial and eight sample networks. Imports Excel, Lotus, dbase, **binary**, and ASIC files. Print/edit neuron matrices.  
(800) 2848112  
EPIC Systems Group  
Neuralyst: Integrates **neural networks** with Excel spreadsheets. Includes macro library for investment analysis.

HNC  
ExploreNet 3000: Windows-based application software program for developing and implementing **neural network** solutions without programming. Database mining program available also.  
(619) 546-8877 / Circle 372  
Hyperlogic

Owl **Neural Network Library**: Twenty-four functions for accessing networks supplied as C library. Twenty types of **neural networks**.  
(619) 746-2765

ImageSoft  
ExperNet: Object-oriented tool for creating Windows-based neural networks and knowledge applications.  
(800) 245-8840

Inductive Solutions  
NNetSheet: Supports nine algorithms for supervised and unsupervised



training . Train network can  
be potted to a spreadsheet.  
(212) 945-0630  
Mathworks

Neural Network Toolbox:  
Includes learning rules,  
transfer functions and train-  
ing and design procedures  
for implementing neural  
networks .  
(508) 653-1415

Martingale Research  
SYSPRO: FORTRAN-based  
neura network simulation  
and prototyping tool.  
(214) 4224570  
Neural Computer  
Sciences

NeuralDesk: Supports  
many algorithms. Manual  
and automatic training of  
neural networks .  
44-703-667775 (UK)  
Neural Systems

Genesis: Development  
environment for interfacing  
neural networks to applica-  
-tion software.  
(604) 263-3667 (Canada)

NeuralWare  
NeuralWorks: Neural net  
-work chip development,  
open architecture, 8-k back  
-propagation , makes net  
-work types from libraries  
and creates diagnostic tools.  
(412) 787-8222

Neurix  
MacBrain: Flexible neural  
connections, activation  
rules, 3-D graphs, interactive  
modeling, visual macro lan-  
-guage.  
(617) 426-5096 1 Circle 381

NeuroDynamX

DynaMind: Train net  
-works on Intel's 80170NX  
ETANN and Intel multichip  
board. Can read and store  
network trained in emula-  
-tion mode and download  
weights to chip.  
(800) 747-3531

NeuroSym  
Neural CASE...

...BPN. CPN, RN, and SOM.  
(713) 523-5777

Peak Software  
Autonet: Constructs net

-works from **training** data  
sets consisting of input vari-  
-ables and expected results.

Networks may also be cre-  
-ated from command line.

(612) 854-0228

SAIC **Artificial Neural**  
Systems

Delta ANSpec: Language  
for defining and implement-  
-ing parallel distributed pro-  
-cessing systems.

(619) 546-6005

Software Bytes

ET 2.0: Simulates text,  
**graphics** and Windows.

Back-error propagation

**neural networks** with Bor-  
-land C/C++ source code, ET

**Graphics** and Windows slide  
**neural networks** on equiva-  
-lent VGA screens

(800) 5214119

Software Frontiers

**Neural Network Toolkit:**  
Development software for  
**neural network** applications.

C source code included.

(800) 475-9082

Talon Development

Brain: Lotus 1-2-3...

...A 5-billion

-connection-per-second  
neurocomputer. The sys-  
-tem has a back-propaga-  
-tion **learning** rate of 1 bil-  
-lion connection updates  
per second.

(503) 690-1236

American NeuralLogix

NLX420: Neural proces-  
-sor slice. A **digital** chip de-  
-signed for real-time **neural**  
**network** systems, This 20-  
-MHz device contains 16 pro-  
-cessing elements, and can  
have up to 64,000 16-bit  
synaptic inputs.

(407) 322-5608

Intel

807170NX ETANN: An elec-  
-trically **trainable** analog  
**neural network** chip. One  
chip can perform over 2 bil-  
-lion multiply-accumulate  
operations per second

(408) 765-9235

Neural  
Semiconductor

CNU3232: **Digital** neural

net chip implements a single-layer network of 32 inputs and 32...

...cmos It has a forward process of 3 billion connections per second and a learning speed of 1.5 billion connections per second.  
(408) 432-8800  
Synaptics

I-1000: Analog neural network chip designed specifically for reading checks. A neural network-based image sensor reads the image and a neural network trained to recognize the characters on a check interprets them.  
(408) 434-0110

DESCRIPTORS: Neural Network ; ...

... Artificial Intelligence ;  
19921000

Set	Items	Description
S1	36989	AU=(ZHANG H? OR ZHANG, H?)
S2	333	AU=(CARLS G? OR CARLS, G? OR GUBERMAN S? OR GUBERMAN, S?)
S3	50	ZHANG(2N)HONG?
S4	0	CARLS(2N)(GARRY OR GARY) OR GUBERMAN(2N)(SHELIA OR SHELIJA OR SHEILA OR SHEILJA)
S5	14832	SVM OR SUPPORT()VECTOR? OR VECTOR()MACHINE?
S6	111	S1:S4 AND S5
S7	35	S6 AND PY<2003
S8	18	RD (unique items)

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8/3,K/4 .(Item 4 from file: 2)

DIALOG(R)File 2:INSPEC

(c) 2005 Institution of Electrical Engineers. All rts. reserv.

7348288 INSPEC Abstract Number: C2002-09-5260B-234

**Title: 3D object recognition for autonomous mobile robots utilizing support vector classifiers**

Author(s): Schwenker, F.; Kestler, H.A.; Simon, S.; Palm, G.

Author Affiliation: Dept. of Neural Inf. Process., Ulm Univ., Germany

Conference Title: Proceedings 2001 IEEE International Symposium on Computational Intelligence in Robotics and Automation (Cat. No.01EX515) p.344-9

Editor(s): Zhang, H.

Publisher: IEEE, Piscataway, NJ, USA

Publication Date: 2001 Country of Publication: USA xiii+560 pp.

ISBN: 0 7803 7203 4 Material Identity Number: XX-2001-02240

U.S. Copyright Clearance Center Code: 0-7803-7203-4/01/\$10.00

Conference Title: Proceedings of 2001 International Symposium on Computational Intelligence in Robotics and Automation

Conference Sponsor: IEEE Robotics & Autom. Soc

Conference Date: 29 July-1 Aug. 2001 Conference Location: Banff, Alta., Canada

Language: English

Subfile: C

Copyright 2002, IEE

**Title: 3D object recognition for autonomous mobile robots utilizing support vector classifiers**

...Abstract: localisation in the camera images, feature extraction, and classification of the extracted feature vectors with **support vector networks**.

Identifiers: **support vector machines ;**

Zhang, H. (editor) 2001

8/3,K/10 (Item 5 from file: 8)  
DIALOG(R)File 8: Ei Compendex(R)  
(c) 2005 Elsevier Eng. Info. Inc. All rts. reserv.

06087894 E.I. No: EIP02287011050

**Title: Motion pattern based video classification using support vector machines**

Author: Ma, Yu-Fei; Zhang, Hong-Jiang

Corporate Source: Microsoft Research Asia, Beijing, (100080), China

Conference Title: 2002 IEEE International Symposium on Circuits and Systems

Conference Location: Phoenix, AZ, United States Conference Date: 20020526-20020529

E.I. Conference No.: 59248

Source: Proceedings - IEEE International Symposium on Circuits and Systems v 2 2002. p II/69-II/72 (IEEE cat n 02ch37353)

Publication Year: 2002

CODEN: PICSDI ISSN: 0271-4310

Language: English

**Title: Motion pattern based video classification using support vector machines**

Author: Ma, Yu-Fei; Zhang, Hong-Jiang

...Abstract: motion pattern descriptor, which can be extracted from shots or video clips. By using kernel **support vector machines** (SVMs), we have devised an optimized multi-class classifier to link low level features with...

Identifiers: Motion pattern based video classification; **Support vector machines** ; Motion texture; Semantic classification scheme

8/3,K/12 (Item 7 from file: 8)  
DIALOG(R)File 8: Ei Compendex(R)  
(c) 2005 Elsevier Eng. Info. Inc. All rts. reserv.

05996508 E.I. No: EIP02046840769

Title: Learning probabilistic distribution model for multi-view face detection

Author: Gu, Lie; Li, Stan Z.; Zhang, Hong-Jiang

Corporate Source: Microsoft Research China, Beijing 100080, China

Conference Title: 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition

Conference Location: Kauai, HI, United States Conference Date: 20011208-20011214

E.I. Conference No.: 58975

Source: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition v 2 2001. p III16-III22 (IEEE cat n PR01272)

Publication Year: 2001

CODEN: PIVRE9 ISSN: 1063-6919

Language: English

Author: Gu, Lie; Li, Stan Z.; Zhang, Hong-Jiang

...Abstract: one of the view classes or into the nonface cls, by using a multi-class SVM array classifier. The classification results from each view are fused together and yields the final...

8/3,K/13 (Item 8 from file: 8)  
DIALOG(R)File 8:Ei Compendex(R)  
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05916031 E.I. No: EIP01436696807

Title: Distance-from-boundary as a metric for texture image retrieval  
Author: Guo, G.; Zhang, H.-J. ; Li, S.Z.  
Corporate Source: Microsoft Research China, Beijing 100080, China  
Conference Title: 2001 IEEE International Conference on Acoustics, Speech,  
and Signal Processing  
Conference Location: Salt Lake, UT, United States Conference Date:  
20010507-20010511  
E.I. Conference No.: 58543  
Source: ICASSP, IEEE International Conference on Acoustics, Speech and  
Signal Processing - Proceedings v 3 2001. p 1629-1632 (IEEE cat n  
01CH37221)  
Publication Year: 2001  
CODEN: IPRODJ ISSN: 0736-7791  
Language: English

Author: Guo, G.; Zhang, H.-J. ; Li, S.Z.  
...Abstract: performance can be improved. The boundaries are obtained by  
using a statistical learning algorithm called **support vector machine**  
( **SVM** ), and hence the boundaries can be simply represented by some  
vectors and their combination coefficients...

Identifiers: Texture image retrieval; Distance from boundary; Texture  
indexing; **Support vector machines** ; Learning similarity



8/3,K/14 (Item 9 from file: 8)  
DIALOG(R)File 8:Ei Compendex(R)  
(c) 2005 Elsevier Eng. Info. Inc. All rts. reserv.

05900345 E.I. No: EIP01416673817

Title: Kernel machine based learning for multi-view face detection and pose estimation

Author: Li, S.Z.; Fu, Q.D.; Gu, L.; Scholkopf, B.; Cheng, Y.; Zhang, H.  
Corporate Source: Microsoft Research China Beijing Sigma Center, Beijing 100080, China

Conference Title: 8th International Conference on Computer Vision  
Conference Location: Vancouver, BC, United States Conference Date: 20010709-20010712

E.I. Conference No.: 58404  
Source: Proceedings of the IEEE International Conference on Computer Vision v 2 2001. p 674-679  
Publication Year: 2001  
CODEN: PICVES  
Language: English

Author: Li, S.Z.; Fu, Q.D.; Gu, L.; Scholkopf, B.; Cheng, Y.; Zhang, H.  
...Abstract: of the facial views or into the nonface class, by using a multi-class kernel support vector classifier (KSVC). Experimental results show that fusion of evidences from multi-views can produce better ...

8/3,K/18 (Item 1 from file: 65)  
DIALOG(R)File 65:Inside Conferences  
(c) 2005 BLDSC all rts. reserv. All rts. reserv.

03562342 INSIDE CONFERENCE ITEM ID: CN037518505

**GACV for** Support Vector Machines

Wahba, G.; Lin, Y.; Zhang, H.

CONFERENCE: Large margins-Workshop

P: 297-310

Cambridge, Mass., MIT Press, 2000

ISBN: 0262194481

LANGUAGE: English DOCUMENT TYPE: Conference Papers

CONFERENCE EDITOR(S): Smola, A. J.

CONFERENCE LOCATION: Breckenridge, CO 1998; Dec (199812) (199812)

NOTE:

Held at the Annual Neural Information Processing Systems conference

**GACV for** Support Vector Machines

Wahba, G.; Lin, Y.; Zhang, H.

Cambridge, Mass., MIT Press, 2000

Set	Items	Description
S1	2713	AU=(ZHANG H? OR ZHANG, H?)
S2	28	AU=(CARLS G? OR CARLS, G? OR GUBERMAN S? OR GUBERMAN, S?)
S3	867	ZHANG(2N)HONG?
S4	51	CARLS(2N) (GARRY OR GARY) OR GUBERMAN(2N) (SHELIA OR SHELIJA OR SHEILA OR SHEILJA)
S5	4792	SVM OR SUPPORT()VECTOR? OR VECTOR()MACHINE?
S6	6	S1:S4 AND S5
S7	2	S6 AND PY<2003
S8	2	RD (unique items)

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    (c) 1999 Business Wire  
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    (c) 1999 PR Newswire Association Inc  
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06224095 SUPPLIER NUMBER: 90469748

**Learning similarity measure for natural image retrieval with relevance feedback. (Abstract)**

Guo, Guo-Dong; Jain, Anil K.; Ma, Wei-Ying; **Zhang, Hong-Jiang**  
IEEE Transactions on Neural Networks, 13, 4, 811(10)  
July, 2002

DOCUMENT TYPE: Abstract ISSN: 1045-9227 LANGUAGE: English  
RECORD TYPE: Abstract

... **Zhang, Hong-Jiang**

...AUTHOR ABSTRACT: images, but also significantly improves the retrieval performance of the Euclidean distance measure. Two techniques, **support vector machine ( SVM )** and AdaBoost from machine learning, are utilized to learn the boundary. They are compared to...

...Index Terms--AdaBoost, constrained similarity measure, content-based image retrieval, feature selection, learning, relevance feedback, **support vector. machine ( SVM )**.

20020701